

Identifying the Relative Contribution of Motoric and Cognitive Engagement on Spatial Memory

by

Yadurshana Sivashankar

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Psychology

Waterloo, Ontario, Canada, 2025

© Yadurshana Sivashankar 2025

Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner: Dr. Lana Trick
Professor Emeritus, Dept. of Psychology, University of Guelph

Supervisor: Dr. Myra Fernandes
Professor, Dept. of Psychology, University of Waterloo

Internal Member: Dr. Jonathan Fugelsang
Professor, Dept. of Psychology, University of Waterloo

Internal Member: Dr. Colin Ellard
Professor Emeritus, Dept. of Psychology, University of Waterloo

Internal-External Member: Dr. Oliver Schneider
Associate Professor, Dept. of Management Science and Engineering,
University of Waterloo

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Contribution of Statement

This research was conducted at the University of Waterloo and University of Bordeaux by Yadurshana Sivashankar under the supervision of Dr. Myra A. Fernandes. Data presented in Chapter 2 was collected at the University of Bordeaux as part of a Mitacs Gloablink funded project awarded to me, Yadurshana Sivashankar. Both Chapters 2 and 3 were published in *Spatial Cognition and Computation* (Sivashankar et al., 2024) and *British Journal of Psychology* (Sivashankar et al., 2025), respectively. Chapter 4 is currently under review at the *Journal of Aging, Neuropsychology, and Cognition*. Portions of this dissertation have been derived from or taken verbatim from these manuscripts.

This research was supported by a Natural Sciences and Engineering Research Council (NSERC) of Canada Graduate Scholarship awarded to me, Yadurshana Sivashankar, and by NSERC Discovery Grant 2020-03917 to Myra A. Fernandes.

Abstract

I investigated the cognitive mechanisms underlying spatial memory, with the aim of differentiating the contributions of motor engagement and decision-making. In Experiment 1, I examined whether volitional motor control or decision-making, during initial exploration of a map within virtual reality, better supported retention of routes travelled. Participants explored virtual cities under three navigation conditions that varied in terms of motor and decision-making demands. During Active navigation, participants had volitional control over their movement using hand-held controllers, allowing head and body rotation in a swivel chair, and made independent decisions about which route to take to reach a target location. During Guided navigation, participants still controlled their movement, but followed a visually guided path overlaid onto the road, eliminating the need for decision-making. In the Passive condition participants observed a pre-defined route without having to make any decisions or engage motorically. Following exploration of each environment, participants were asked to “re-trace their steps” using the exact route they had just traveled, from the same starting point. Route memory was significantly better following Active and Guided encoding relative to Passive, suggesting that volitional movement during navigation underlay the benefit. Notably, the complexity of the path chosen by participant at encoding did not predict accuracy of route memory. Experiment 2 assessed the necessity of motor engagement and decision-making by comparing memory benefits following two types of VR implementation: Desktop-VR, in which movement was limited to keyboard input (lower motor engagement), and Headset-VR, in which participants navigated using a steering wheel (higher motor engagement). An effect of navigation strategy emerged only in the Headset-VR group: Active and Guided navigation at encoding led to significantly better route memory relative to Passive. No significant differences emerged between Active and Guided trials, suggesting that motoric engagement, rather than decision-making, is the driver of memory performance. Interestingly, in Headset-VR, a stronger personal preference for Active exploration predicted better route memory, whereas in Desktop-VR, personal motivation predicted route memory accuracy. However, neither motivation nor preference mediated performance, indicating that these factors did not account for the effect of navigation condition on memory. If motor engagement contributes to the formation of route memories, as suggested by experiments 1 and 2, then reduced mobility in older adults may influence performance, and the components underlying it. At the same time, reliance on landmark memory to guide memory may be heightened, as landmarks provide salient external cues that could compensate for reduced motor-based encoding. To test these predictions, in Experiment 3 I examined route and landmark memory in younger and older adults as they explored virtual environments. In younger adults, both Active and Guided navigation equally enhanced memory for routes compared to Passive, replicating

experiments 1 and 2. However, in older adults only Active navigation, which engaged both movement and decision-making, resulted in improved route memory. Further, landmark memory in older adults benefitted the most from Active relative to Passive and Guided navigation. Simply put, active encoding eliminated age-related deficits in route memory, suggesting that decision-making (present only in this condition) during navigation may be particularly important for supporting spatial memory in aging populations. This benefit may reflect increased recruitment of frontal lobe-based resources during active navigation, which can compensate for reductions in motor engagement. There were some differences in motivation and preference ratings across conditions in both age groups. However, these subjective measures did not emerge as significant predictors of memory performance. Overall, my findings suggest that motor engagement plays a more critical role than decision-making in enhancing subsequent route memory in younger adults, whereas conditions that require decision-making benefit memory in older adults. These findings have important implications for the design of navigational tools and cognitive interventions aimed at promoting spatial independence, particularly among older adults.

Acknowledgements

First and foremost, this dissertation would not have been possible without the support and dedication of my graduate supervisor, Dr. Myra Fernandes. Her feedback, encouragement, funding support, and guidance, both academic and personal, have been instrumental over the past six years. She has always been fair and honest, consistently challenging me to grow as a scholar. Myra is not only an exceptional academic but also an extraordinary mentor, and I aspire to follow her example in my own career. I would also like to thank Dr. Hélène Sauz  on, who was a supportive supervisor during my time as a visiting scientist at the University of Bordeaux. Her commitment was invaluable in helping me set up my first PhD experiment in France, especially when I was still unfamiliar with the school system. She kindly showed me around the campus and introduced me to her lab, who were all so welcoming and generous in sharing their space. I am truly grateful to have had this opportunity during my PhD studies. I would also like to thank my examining committee for their thoughtful feedback and encouragement.

On the home front, I would like to thank my mom, dad, brother, sister-in-law, and grandma. Their unconditional love and support throughout my graduate career made it possible for me to finish. They were always there for me during difficult times and encouraged me to never give up. This PhD would not have been possible without their love. I am forever grateful to have such a loving and supportive family. I am deeply grateful to Madusha for supporting me through challenging times and for our long coffee dates that never failed to lift my spirits.

I am also grateful to my dedicated research assistants over the years for their help gathering materials, collecting data, and providing feedback on my studies: Philip He, Lena Coulon, Victoria Bernado, Evan Skorski, Janelle Clarke, and Jhanvi Mauree. I would also like to extend my sincere thanks to my lab mates and collaborators Dr. Brady Roberts, Sophia Tran, Khalil Hussein, Brian Kim, Tala Tayem, and Patrick Tsapoitis, for their thoughtful feedback while we shared a lab together.

Dedication

To my parents, for their love and support.

Table of Contents

Examining Committee	ii
Author's Declaration	iii
Abstract	v
Acknowledgements	vii
Dedication	viii
List of Figures	xiii
List of Tables	xv
1 General Introduction	1
1.1 Historical context	1
1.2 Active versus Passive Navigation	2
1.2.1 The Role of Decision-making in Active Exploration	3
1.2.2 A Role for Motor Engagement in Spatial Memory	5
1.3 Aging and Spatial Memory	6
1.4 Individual Differences in Spatial Memory	7
1.5 Present Investigation	8

2	Motoric Engagement, But Not Decision-Making, During Encoding Influences Route Memory	11
2.1	Introduction	11
2.1.1	Current Study	12
2.2	Methods	13
2.3	Results	20
2.3.1	Route Overlap Memory Performance	20
2.3.2	Difference in Self-reported Levels of Motivation and Preference to Explore	21
2.3.3	Correlation Between Route Overlap Score and Individual Difference Measures	23
2.3.4	Assessment of Path Complexity Across the Three Exploration Conditions	23
2.4	Discussion	26
2.4.1	Limitations	27
2.4.2	Conclusion	28
3	The Necessity of Motoric Engagement in Enhancing Route Memory	29
3.1	Introduction	29
3.1.1	Method of Implementation: Desktop Versus Headset-based Viewing Within VR	30
3.1.2	Current Study	32
3.2	Methods	33
3.3	Results	40
3.3.1	Route Memory Performance	40
3.3.2	Self-reported Motivation	43
3.3.3	Self-reported Preference	44
3.3.4	Assessment of Path Complexity	45
3.3.5	Correlations with Individual Difference measures	48

3.3.6	Predictors of Route Memory Performance	51
3.3.7	Exploratory Mediation Analysis	52
3.4	Discussion	54
3.4.1	Possible Neural Mechanisms Underlying Navigation	55
3.4.2	The Role of Individual Differences in Spatial Navigation	56
3.4.3	Conclusion	58
4	The use of decision-making to mitigate age-related differences in spatial memory	59
4.1	Introduction	59
4.1.1	Current Study	60
4.1.2	Individual differences	61
4.2	Methods	62
4.3	Results	68
4.3.1	Route Overlap (memory) Performance	68
4.3.2	Landmark Memory Performance	70
4.3.3	Assessment of Path Complexity	72
4.3.4	Self-reported Motivation	73
4.3.5	Self-reported Preference	73
4.3.6	Predictors of Route Memory Performance	74
4.4	Discussion	75
4.4.1	Neural Mechanisms in Younger Adults: The Role of Motor Engagement	75
4.4.2	Neural Mechanisms in Older Adults: The Importance of Agency . .	77
4.4.3	A Role for Individual Differences in Spatial Memory	78
4.4.4	Conclusion	79

5	General Discussion	80
5.1	Motion Cues as a Foundation for Route Memory	81
5.2	The Importance of Type of Retrieval Test	83
5.3	Decision-Making as a Key Determinant of Route and Landmark Memory in Aging	84
5.4	The Interplay between Individual Differences and Spatial Memory	85
5.5	Future Directions	86
5.6	Implications for Navigation Aids and Cognitive Training	87
5.7	Conclusion	88
	References	89
	Appendix	99

List of Figures

Figure 1. Panel A: Example of paths travelled in one of the virtual environments at encoding and retrieval, showing perfect route overlap (good memory for route travelled at encoding).	17
Figure 1. Panel B: Example of paths travelled in one of the virtual environments at encoding and retrieval, showing significant path deviation (poor memory for route travelled at encoding).	17
Figure 2. From left to right: passive, guided (movement was controlled via the handheld controller), and active (movement was controlled via the handheld controller) navigation conditions.	19
Figure 3. Route overlap (measured by deviation distance between path travelled at encoding and retrieval) score across Passive, Guided, and Active conditions.	21
Figure 4. Mean motivation and preference scores for Passive, Guided, and Active conditions.	22
Figure 5. Sample of a participant's path complexity and percentage (shown underneath) of each environment explored, with Passive condition shown in black, Guided condition in green and Active condition in blue.	25
Figure 6. Display seen in the Desktop-VR group. From left to right: Passive, Guided, and Active Navigation Types.	38

Figure 7. Display during Headset-based VR. From left to right: Passive, Guided, and Active Navigation Types.	39
Figure 8. Route overlap (measured by deviation distance between path travelled at encoding and retrieval) score in Passive, Guided, and Active conditions.	41
Figure 9. Panel A. Path complexity and percentage score (shown underneath) from a sample participant from the Desktop-VR group, with Passive trials shown in black, Guided trials in green and Active trials in blue.	46
Figure 9. Panel B. Path complexity and percentage (shown underneath) from a sample participant from the Headset-VR Group, with Passive trials shown in black, Guided in green and Active in blue.	47
Figure 10. Mediation model for Desktop-VR group examining whether the effect of navigation type (Active as reference; Passive, Guided) on Route Memory was mediated by self-reported motivation to explore under each navigation type. Standardized Linear Regression Coefficients (β) along with confidence intervals (based on 5000 bootstrap re-samples) and p-values are shown.	53
Figure 11. Mediation model for Headset-VR group examining whether the effect of navigation type (Active as reference; Passive, Guided) on Route Memory was mediated by self-reported motivation to explore under each navigation type. Standardized Linear Regression Coefficients (β) along with confidence intervals (based on 5000 bootstrap re-samples) and p-values are shown.	54
Figure 12. Route deviation in Passive, Guided, and Active conditions in younger and older adults.	70
Figure 13. Memory for landmarks (measured by hit rates for targets correctly recognized following encoding) contained within environments explored using Passive, Guided, and Active navigation conditions in younger and older adults.	71

List of Tables

Table 1. Individual difference measures from participants in the desktop-VR and headset-VR groups.	34
--	----

Table 2. Mean motivation and preference scores in each VR group, following each navigation condition.	43
---	----

Table 3. Pearson correlations in each group showing association between route memory following each navigation condition and various individual difference measures. ...	49
---	----

Table 4. Mean motivation and preferences scores in each age group, following each navigation condition.	74
---	----

Chapter 1

General Introduction

1.1 Historical context

Spatial navigation is a vital cognitive skill that enables individuals to move through and interact with their environment (Appleyard, 1970; O'Malley, 2018). It plays a significant role in daily activities such as commuting, navigating unfamiliar areas, and remembering the layout of buildings. Recent advances in technology have attempted to make this complex task simpler by offering users systematic turn-by-turn directions (Gardony et al., 2013). Using a navigation aid allows individuals to input a destination and receive direct guidance. For instance, with Google Maps[™], a user can input the final address and obtain step-by-step directions to reach it. While this is highly convenient and especially helpful in unfamiliar environments, it remains unclear how this form of cognitive offloading impacts our memory for spatial information. For instance, Ishikawa (2019) has shown that the long-term use of navigational aids impairs performance on wayfinding tasks, assessed by travel time, the number of stops, and travelling in the opposite direction to the end point. Global configural knowledge about the explored environment was also impaired (Ishikawa, 2019). To counteract these negative effects, some have suggested it would be beneficial for users to actively invest mental effort during a wayfinding task, to reduce the negative impact of automated visual- and audio-based navigation tools on memory for a route travelled (Dahmani & Bohbot, 2020; Gardony et al., 2013, Parush et al., 2007). To this end, the broad objective of this thesis was to understand the cognitive mechanisms underlying successful retention of spatial knowledge in order to assess the impact of guided navigation on spatial memory.

1.2 Active versus Passive Navigation

One approach for understanding spatial navigation is through the lens of active versus passive exploration (Dahmani & Bohbot, 2020; Gardony et al., 2013). In the literature, active navigation is said to involve both cognitive (mental manipulation of spatial information, allocation of attention, and decision-making) and physical (motor control for locomotion, proprioceptive, and vestibular sensory information) components (Chrastil & Warren, 2012). Put simply, walking to the nearby grocery store is a perfect example of active exploration, as it requires you to remain aware of your surroundings, while also initiating the correct sequence of actions to reach your destination. In some cases, you might even decide to take a shortcut to the grocery store if you encounter a train crossing and see a train passing. In these situations, you are motivated to reach the store and must engage in mental manipulation of the environment, allocate attention, make decisions at key intersections, and activate motor control for locomotion.

On the other hand, passive navigation is said to require very little cognitive and motor effort (Chrastil & Warren, 2013). This type of navigation is similar to being a passenger on a bus. You may be visually aware of your surroundings, but you are not actively moving your body or making directional decisions. In fact, Appleyard (1970) was one of the first researchers to demonstrate that bus passengers retain little knowledge of the broader spatial environment, whereas drivers, who actively make their own navigational decisions, develop greater survey knowledge, a global, bird's-eye view of routes and spatial relationships within a city. This distinction aligns with differences in spatial referencing: passive travelers rely primarily on egocentric cues tied to their immediate viewpoint, whereas active navigators engage allocentric processing, allowing them to build more stable, map-like representations of the environment. Indeed, the seminal study by Maguire and colleagues (2006) revealed that taxi drivers with several years of navigation experience exhibited additional gray matter volume in mid-posterior hippocampi and less volume in anterior hippocampi. This finding reveals the hippocampus to be a critical structure underlying flexible spatial learning and memory, promoting the ability to integrate routes into a coherent cognitive map of the environment.

With the advent of GPS devices, we now have a new type of navigation aid to consider when studying spatial memory. That is, we must now consider the effects on memory when one is navigating under the direct influence of a GPS aid. Here, decision-making is removed from the navigator, but motor engagement still required.

1.2.1 The Role of Decision-making in Active Exploration

Decision-making in particular has been predicted to be a key component in successfully acquiring spatial knowledge about an environment (Carassa et al., 2002; Farrell et al., 2003; Stulpnagel & Steffens, 2012). For example, Munzer and colleagues (2006) found that a mobile navigation device that presented systematic route directions during navigation impaired later landmark, relative to the use of a physical map. The authors interpreted the benefit afforded by map-guided navigation (i.e., physical map) as due to the cognitive effort required by the participant. That is, a physical map required one to develop an integrated representation of landmarks represented along routes, and to transfer this information to route choices (decision-making) in the real environment. Engaging such cognitive processes is believed to have facilitated memory.

Similarly, Gardony and colleagues (2013) provided verbal navigation commands (e.g., “Forward”, “Slightly to the right in 100 ft”) every five seconds as participants explored virtual environments. These researchers found that the presence of a navigational aid impaired spatial memory assessed by recall of landmarks, and accuracy in later map drawings. They suggested that providing directional instructions in advance impairs participants’ ability to form a coherent mental representation of routes travelled and to successfully encode the nearby landmarks specific to that route and location. Put another way, listening and holding verbal commands in working memory during navigation is believed to compete for cognitive resources needed to retain an accurate representation of the spatial information.

Further, in a study conducted by Bakdash and colleagues (2008), participants’ memory for the spatial layout of a virtual environment was assessed after encoding various environments in one of three ways: (1) active exploration involving both decision making and motor control, (2) deciding the path of travel with no volitional motor control [i.e., “backseat driver”] and (3) controlling a joystick for movement while receiving directions (no decision-making). During the test phase, spatial knowledge was measured by having participants point to target locations previously seen during exploration. Bakdash and colleagues (2008) found that pointing accuracy to target locations was comparable when the virtual environments were encoded under active navigation, and when decision-making was employed at encoding in the absence of motor control. In other words, simply exerting motor control did not benefit spatial memory. It is important to note, however, that the results observed by Bakdash and colleagues (2008) pertain specifically to memory for selective locations, as opposed to route memory, since participants had to simply point to target locations in a scene rather than demonstrate memory retention of a route.

Chrastil and Warren (2015) also found decision making was a key component of active learning for the acquisition of graph knowledge (known connectivity of the environment,

encompassing all routes). They examined the roles of visual information, idiothetic cues (e.g., motor/proprioceptive cues), and cognitive decision-making in acquiring topological graph knowledge. In a Desktop-VR setting ¹, participants learned object locations in a virtual maze either by walking or watching a video, while making their own path decisions or being visually-guided. Graph knowledge was then assessed using a shortest route task, in which the participant walked through the corridors of the maze from a starting object to the remembered location of a target object. Results revealed decision making, rather than idiothetic cues, to be the primary contributor to graph knowledge. This type of task, as described in their study, does not assess the exact memory for a route travelled, but rather the ability to integrate knowledge of various known paths to take novel routes (i.e., graph knowledge).

These studies collectively emphasize the important role of decision-making to spatial memory, particularly for broader survey and graph knowledge. Route knowledge on the other hand, entails the recollection of specific actions (e.g., turning left or right) at particular decision points along a route (see Chrastil & Warren, 2012 for review). Hence, it is possible to remember turns solely based on one’s initial motoric or procedural memory for the paths taken. To date, researchers have not examined route retrieval using a series of ecologically valid experiments conducted in virtual reality environments that closely simulate real-world city navigation. Given the current gaps in the literature, it is worthwhile to assess route memory under distinct navigation conditions that differ in the use of motor engagement and decision-making in order to better understand the cognitive mechanisms underlying this form of spatial memory. To this end, one of the aims of this thesis was to examine whether visually guided exploration in which a participant exerted motor control to explore a prescribed route, in the absence of decision-making, hindered route memory relative to active and passive navigation. This is an important question to address as navigation use has increased considerably in the recent years, and it is still unclear in the literature whether route memory, in particular, is dampened by the use of a navigation aid.

¹Desktop VR refers to a virtual reality system that is experienced on a standard computer screen (desktop or laptop) rather than through an immersive head-mounted display (HMD). In Desktop VR, users interact with a virtual environment using conventional input devices such as a keyboard, mouse, or game controller, and the environment is viewed through a standard monitor rather than being “surrounding” them in 3D space (Chrastil & Warren (2015)).

1.2.2 A Role for Motor Engagement in Spatial Memory

Another viewpoint to consider when understanding spatial navigation is the egocentric frame of reference. The egocentric system operates from a first-person perspective, where individuals rely on their body movements and sensory feedback, such as proprioception and vestibular cues, to navigate and determine their location (Epstein et al., 2017). The allocentric frame of reference, in contrast, utilizes a top-down perspective, relying on external landmarks to orient oneself in space. Both systems work together to create a comprehensive spatial map. A key difference between these frames is the type of cue supporting each frame of reference. Egocentric navigation depends on inertial cues that engage the dorsal striatum, supporting the encoding of routes and procedural memories. These cues include proprioceptive feedback, vestibular signals, and accelerative cues, all contributing to the perception of self-motion. In contrast, allocentric navigation is enhanced when individuals freely make decisions about their path, connecting landmarks and routes to form a global spatial representation of the environment.

Successful navigation incorporates both cognitive (e.g., mental manipulation of spatial information, decision-making) and motoric (e.g., proprioceptive and vestibular sensory feedback) components (for a review see Cullen & Taube, 2017). These components are believed to combine to create a multi-modal representation of the environment. For example, motor information gathered during exploration through self-motion cues (such as head turns and body movements) plays a significant role in encoding spatial information, particularly to route memory (for a review see Cullen & Taube, 2017). Cognitive functions like decision-making, attention, and mental manipulation are managed by the frontal lobes and hippocampus, forming allocentric representations of space and helping us remember specific landmarks and routes (Jerald & Marks, 2016).

In addition, research with rodents has also underscored the importance of motor cues in supporting spatial memory (Vorhees & Williams, 2014). For instance, self-motion cues, especially vestibular and proprioceptive signals, have been shown to be essential for navigation (Waller & Nadel, 2013). The vestibular system, which contributes to balance and motion detection, and proprioception, which provides feedback about limb and body position, are both critical for encoding spatial information. Studies have demonstrated that damage to either system significantly impairs animals' ability to navigate and form accurate mental representations of their environment (Coto et al., 2021). These findings suggest that motoric engagement is not merely supportive but fundamental to spatial memory formation.

If motor control underlies route memory, then older adults who show age-related motor decline may not benefit from encoding conditions that only promote motor engagement.

Instead, they may particularly need, and benefit, from active navigation conditions that encourage self-initiated decision-making. Specifically, because older adults experience decline in key brain regions involved in decision-making and spatial learning, such as the frontal lobes and medial temporal lobe structures, relying heavily on devices for navigation may impair their ability to remember routes and to associate landmarks with specific paths that support memory (Buckner, 2004; Konishi & Bohbot, 2013). A second goal of this thesis was to examine whether older adults distinctively benefit from active navigation strategies that engage decision-making, compared to guided and passive conditions that limit such involvement.

1.3 Aging and Spatial Memory

Healthy aging is accompanied by a variety of neural changes, with the frontal lobes and hippocampus being especially vulnerable (Raz et al., 2005; Park & Reuter-Lorenz, 2009). These changes are not merely structural but have functional consequences that affect cognition and adaptability. For example, Raz and colleagues (2005) conducted a longitudinal study demonstrating significant shrinkage in regions such as the caudate, cerebellum, hippocampus, and association cortices, with the hippocampus showing an annual atrophy rate of approximately 0.86%. This neurodegeneration is associated with observable difficulties in forming and retaining spatial memories (Buckner, 2004; Harris & Wolbers, 2012; Rosenbaum et al., 2012).

These declines extend beyond memory and impact quality of life, as impaired spatial abilities can reduce older adults' ability to engage in everyday activities such as social outings, attending appointments, and walking. Functional imaging studies have found that, during memory encoding, older adults show heightened activation in frontal regions (Cabeza et al., 1997; Cabeza, 2002) but reduced activation in medial temporal areas, including the hippocampus (Grady et al., 1995; Daselaar et al., 2003; Park & Gutchess, 2004). These patterns are believed to reflect compensatory mechanisms, where frontal recruitment attempts to overcome declining hippocampal-based memory functioning (Park & Reuter-Lorenz, 2009). The success of this compensation is thought to depend on lifestyle factors such as education, physical activity, cognitive engagement, and nutrition (Buckner, 2004; Gutchess et al., 2005). Importantly, these neural patterns differ between high- and low-functioning older adults: high-functioning individuals tend to show more effective frontal compensation and better-preserved hippocampal engagement, whereas low-functioning adults exhibit weaker compensatory recruitment, leading to greater spatial difficulties and steeper declines in everyday navigation (Buckner, 2004).

In addition to neural decline, aging is also marked by reductions in motor function, including slower coordination and diminished proprioceptive sensitivity (Park, & Gutchess, 2004; Park, & Reuter-Lorenz, 2009; Ward and Frackowiak, 2003). These changes further impair an individual’s ability to navigate effectively. Older adults may find it difficult to rely on the proprioceptive and vestibular cues that support spatial encoding in younger populations (Park, & Gutchess, 2004; Park, & Reuter-Lorenz, 2009). In addition, age-related declines in executive functioning and decision-making may hinder performance tasks that require integration of movement and spatial reasoning, such as identifying alternate routes or recalling directions in unfamiliar environments.

Despite these challenges, emerging evidence suggests that targeted engagement in decision-making tasks during navigation may help mitigate spatial memory decline in older adults (see review by Fricke et al., 2022) . Studies comparing young and older participants have shown that requiring decisions during route learning can improve memory for older adults, potentially compensating for declines in motoric input. For example, in the study by Meade and colleagues (2019), both younger and older adults explored novel spatial routes that were either actively or passively encoded. During active encoding, participants decided the route of travel and exerted volitional control of their movements by using a button press. Passive exploration simply consisted of viewing a pre-selected route. During retrieval, participants were placed in the same starting location and asked to retrace the previously traveled route. Findings revealed that active navigation, compared to passive viewing during encoding, resulted in a higher accuracy in spatial memory, with the magnitude of this memory enhancement being significantly larger in older than in younger adults. This suggests that decision-making processes, particularly those supported by frontal lobe activation during active exploration, may serve as a critical buffer against age-related spatial memory loss.

1.4 Individual Differences in Spatial Memory

In addition to spatial memory performance, I was also interested in documenting any individual differences in the influence of each navigation condition on memory. After participants completed the exploration and retrieval phases in VR, I asked them to complete a questionnaire probing for individual differences in everyday navigation proficiency as measured by the *Santa Barbara Sense of Direction Scale* (Hegarty et al., 2005; SBSODS).

I also measured whether there were any differences in self-reported levels of motivation and preference to explore in one of the three navigation conditions (passive, guided, and active). Past studies have reported a critical role for motivation in enhancing spatial memory

in children, younger, and older adults (Gruber et al., 2014; Sakaki et al., 2018; Sivashankar et al., 2024). For example, Gruber and colleagues (2014) have suggested that we better encode information that we are motivated to acquire because it better engages attention, promotes exploration, and leads to information-seeking behaviour, ultimately enhancing memory. This neurocognitive framework stresses the interplay between motivation and the so-called reward networks in the brain, whereby motivation induces a state of curiosity that enhances memory through the release of dopamine in the hippocampal memory system (Lisman & Grace, 2005). Further, prior studies have linked hippocampal volume and blood flow to ‘active’ navigation. That is, when motor control and decision-making are required at exploration (Javadi et al., 2017; Konishi and Bohbot, 2013; Maguire et al., 2000) these indices increase. In light of these findings, I predicted that hippocampal-mediated memory for a route travelled (Jansen-Osmann & Wiedenbauer, 2004) would be better remembered if greater motivation is reported for a given navigation condition. I was interested in determining whether participants were more motivated to explore in the active and guided conditions, relative to passive, as this could be sufficient to explain any subsequent benefit to memory. Finally, I measured simulator sickness (Kennedy et al., 1993; *Simulator Sickness Questionnaire*) and one’s sense of presence in VR to assess the “realness” of the virtual environments (Schubert et al., 2001; *Igroup Presence Questionnaire*). This too could indirectly influence memory performance for the routes travelled in VR.

1.5 Present Investigation

One of the objectives of the present thesis was to examine whether motor engagement or decision-making plays a more central role in supporting spatial memory, particularly in route learning contexts. To address this, Chapter 2 explored spatial memory under three navigation conditions: Active, Guided, and Passive.

In the Active condition, participants navigated freely through a virtual environment, requiring both motor engagement and decision-making during encoding. In the Guided condition, participants followed a visual cue to the destination, requiring motor engagement (i.e., pressing the trackpad of the VR controller to move) but not independent decision-making. In the Passive condition, participants are passively transported along the route, removing both motor and decision-making components. This design allowed for a systematic investigation of whether varying the level of motoric engagement at encoding affected route memory performance, assuming motor cues played a central role in spatial learning.

Another reason to examine guided navigation and route memory was that relying on

external devices to reduce processing demands may negatively affect memory performance. For example, Risko and Gilbert (2016) define cognitive offloading as the use of physical action or affordances of the external environment to modify the cognitive demands required by a task. An example of a physical action is using fingers to solve simple arithmetic calculations or using gestures to convey meaningful information during speech (Novack & Goldin-Meadow, 2015; Sivashankar & Fernandes, 2022; Sivashankar et al., 2023). That is, offloading to the external environment involves using an external repository to hold information, or to help us retrieve information (see Risko & Gilbert, 2016 for review). Without an external aid one must register, rehearse, and maintain an internal representation of the information. Past research examining the negative impact of offloading on human cognition has found that memory for the offloaded information is poor in participants who saved to-be-remembered items on a computer, relative to individuals who had to commit the target items to memory (Sparrow et al., 2011). Similarly, I too predicted that the presence of a navigational aid might impair memory for routes travelled, relative to when one explored without such an aid.

A second objective was to examine how these navigation strategies affected older adults, a group for whom both motoric and executive functioning are known to decline. There is reason to believe that older individuals may gain differentially from active navigation strategies that allow for self-initiated decision-making about the travel path, and would suffer when decision-making is removed, as in cases of guided navigation. For example, neural evidence shows that self-initiated decision-making during navigation strengthens connectivity between frontal and hippocampal regions (Euston et al., 2012; Konishi & Bohbot, 2013); these are the brain areas subject to the most deterioration as a result of aging. As well, other research suggests that having a sense of agency, which is limited when using GPS devices, can serve to benefit memory (Hon & Yeo, 2021). Similarly, research has shown that a lack of perceived control can reduce memory in older adults (Lachman & Agrigoroaei, 2012), therefore the use of GPS may have negative consequences. Together, these investigations aim to clarify the cognitive mechanisms that best support spatial memory and inform strategies for maintaining navigational independence in older age.

Beyond route memory performance, I also examined item recognition memory for landmarks encountered during exploration. Specifically, in Chapter 4, both younger and older adults were asked to identify target landmarks from the environments they explored. Landmark memory is an essential component of spatial memory, as it involves recalling key buildings, objects, and items that can serve as cues to selectively remember routes and the broader spatial layout (Richter & Winter, 2014). Neuroimaging research has identified the parahippocampal region as central to landmark processing (Liang et al., 2023; Sun et al., 2021). In an aging population that increasingly relies on contextual cues to

support memory encoding, I sought to investigate potential age differences in landmark memory performance. Although neural tissue surrounding the parahippocampal region may undergo age-related atrophy, prior studies suggest that older adults are more likely than younger adults to actively use contextual cues to anchor themselves in space (Anderson & Craik, 2017; Fricke et al., 2002), potentially enhancing subsequent landmark memory. Moreover, I was also interested in learning how different navigation strategies such as passive, guided, and active exploration, will influence landmark memory. If the mechanisms underlying landmark memory are parallel to those of route knowledge, which prior human and animal studies show depend on motoric input, then a similar effect of navigation condition on performance would be expected. However, if landmark memory relied on distinct neural systems from route memory, then navigation strategy may exert a differential influence on memory for landmarks. Examining different types of spatial memory under the three navigation conditions offered a clear insight into the cognitive mechanisms required by each.

Chapter 2

Motoric Engagement, But Not Decision-Making, During Encoding Influences Route Memory

2.1 Introduction

In trying to understand factors that influence memory for routes travelled, past studies have suggested significant spatial memory benefits when encoding is ‘active’ rather than ‘passive’ (Chrastil & Warren, 2012; Jebara et al., 2014; Meade et al., 2019; Sauz  on et al., 2016). That is, spatial learning is significantly impaired when individuals passively view routes, as in the case of a passenger who is simply observing a path, relative to a driver who actively initiates their own decisions about where to explore and how to arrive at a location (see Chrastil & Warren, 2012 for review).

The benefits of active exploration are thought to arise from both cognitive processes such as mental rotation, attentional allocation, and decision-making, and physical components, such as motor control for locomotion as well as proprioceptive and vestibular inputs (Chrastil & Warren, 2012). It is unclear, however, which of these components drives the benefit of active exploration on subsequent memory for routes travelled. That is, is it the motor or the decision-making aspect of active navigation that is critical? Some suggest decision-making is a key component in successfully acquiring spatial knowledge about a map (Carassa et al., 2002; Farrell et al., 2003; Stulpnagel & Steffens, 2012). On the other hand, Day and Fitzpatrick (2005) and Smith (2017) have shown that body-based motor

cues arising from proprioceptive and vestibular systems, engaged during encoding, are critical to spatial navigation. Spatial navigation requires the continuous integration of visual information, along with vestibular and proprioceptive cues, to enable both purposeful and safe navigation (for a review see Cullen & Taube, 2017).

Relatedly, it is unclear whether following directions provided by an external aid helps or hinders later route memory, as this type of guided navigation retains volitional control of movement, but removes decision-making (i.e., self-directed choice). In the current Experiment, the way in which we provided directions during the guided navigation condition differed in two critical ways from past studies: first, participants received a visual cue (shown in the colour yellow, directly overlaid on the path to be taken) directing them to the correct route to find the target object (a gold star). Second, participants did not need to hold verbal instructions in working memory, as they simply had to follow the visual cue that was always present in the form of an overlaid path. Importantly, I believe that the guided navigation condition used in the current Experiment better reflected how driving directions are provided in the real world, as navigational guidance in the form of a visual cue or verbal commands are always present and available to the driver (no working memory load). Thus, the aim of this chapter was to investigate whether guided exploration, a navigation type that is analogous to following systematic directions from a GPS, hindered route memory.

2.1.1 Current Study

In the current study, I was particularly interested in route memory, to better understand the possible consequences of following systematic directions from a GPS. Route memory requires the successful retrieval of precise place and specific action sequences at identifiable locations or decision points (Malley et al., 2018). To examine this research question, participants explored 12 environments within virtual-reality (VR) in one of three ways: (1) viewing a video of a pre-recorded path with no volitional motor control (hereafter referred to as ‘passive’), (2) freely exploring an environment while making decisions about where to turn and how to arrive at a location (hereafter referred to as ‘active’), or (3) receiving visual guidance to a final destination (hereafter referred to as ‘guided’). The use of VR allowed me to simulate real-world environment layouts of cities around the world (e.g., Tokyo, New York), and to examine both the physical and cognitive contributions to route memory. To assess memory for routes travelled at encoding, participants were placed at the exact same starting position within each VR environment, and were instructed to reproduce the path they had taken during initial exploration. This novel approach enabled me to accurately measure route memory in VR.

There is a possibility that removing decision-making during exploration could limit creation of a mental representation for the routes explored. For example, some researchers have noted that decision-making during navigation requires one to draw on previous experiences to inform navigational decisions (Shohamy & Daw, 2015). It is believed that the self-referential cues evoked by a requirement to decide, then enhances memory for those key decision points when called to retrieve. Further, it is well-known that the medial pre-frontal cortex (mPFC) plays a critical role in decision-making (Euston et al., 2012). Recent studies suggest the involvement of mPFC in strengthening hippocampal-dependent memories for events which require decision-making (Sul et al., 2010). The strong network connectivity between the ventral half of the hippocampus (critical for encoding spatial locations via place cells) and mPFC offers further anatomical evidence of this interaction (Preston & Eichenbaum, 2013; Shin et al., 2019). Thus, it is possible that active navigation could confer the greatest benefit to route memory, followed by guided and then passive exploration.

On the other hand, it is important to note that efferent motor commands that determine the path of travel during volitional motor control are also suggested to be critical in mediating the benefit of active navigation to spatial learning (Chrastil & Warren, 2012). Notably, past work in humans has shown that successful representation of a cognitive map involving both landmark and route knowledge exclusively relies on the intact functioning of the vestibular system and other body-based motor cues (Jabbari et al., 2021; Waller et al., 2004). Thus, it is possible that memory in the guided condition would be similar to that in the active one if these motoric contributions outweigh the cognitive, decision-making, contribution. Thus, I examined whether a navigation type that engaged the motoric system at encoding, in the absence of decision-making, conferred a benefit to memory proportional to active navigation.

2.2 Methods

Participants. After conducting a power analysis using G*Power software (version 3.1), a sample size of 43 participants or greater was deemed necessary to achieve 90% power to detect a medium-sized (Cohen’s $d = 0.5$) main effect in a within-subjects design (i.e., a one-way repeated measures), with an alpha level of 0.05 (Field, 2005). Fifty undergraduate students (30 males, 20 females; $M_{age} = 22.0$, $SD = 2.20$) from the University of Bordeaux in the New-Aquitaine region of France, were recruited on a volunteer basis to participate in the study. The Research Ethics Committee at University of Bordeaux and University of Waterloo approved all study procedures. Written informed consent was obtained from

all participants prior to experimentation. Data collection took place between March and August of 2022.

Materials. VR application: A computer-run VR application was designed on the 3D Unity © engine (ver. 2019.4.4f1; see specifications on <https://www.vive.com/ca/>), using the software Mapbox (<https://www.mapbox.com/>). Mapbox generates game objects for roads and structures using open-source geolocation data and 3D scans of buildings, requiring a GPS position and a zoom scale to specify the perimeter of the location that is being simulated. Unity © engine is a game development platform used by game designers to create virtual environments for players to explore. In my experiment, I paired a VR immersion plugin with 3D Unity © engine that generated game objects using geolocation data from real cities, creating an application that allowed participants to use VR headsets to virtually explore custom-created 3D environments based on real-world environment layout of selected cities.

The VR application included 12 Virtual Environments (VEs) created by entering the longitudinal and latitudinal coordinates of various cities around the world (e.g., Abu Dhabi, Chicago, Grenoble, London, Manhattan, Prague, Rio de Janeiro, San Francisco, Singapore, Sydney, Tokyo, Windsor) into the Mapbox Environments SDK for Unity © engine. My VR application allowed participants to explore VEs with a lightweight HTC VIVE headset (HTC Corporation; Valve Corporation) and handheld controllers, with continuous button press and heading rotation, for an easy-to-use control interface. Environments in my VR program were chosen to contain sufficient path complexity, and to be equivalent in environment sizes. Path complexity was operationalized to be the number of intersections (i.e., total possible turns) contained in each environment. Google Maps Street™ View was then used to decide specific streets within an environment to include in my VR program. Environments were all topographically (i.e., structural organization of the environment) similar, with an average area of 100,000 square meters (measured using Google Earth™ polygon tracing) with a minimum of 4 and a maximum of 20 intersections (point at which two or more roads converged). Since I created the environments to simulate how the cities appear in the real world, some environments contained a greater number of intersections than others¹. Following environment selection, I integrated landmarks into each environment according to observations made from Google Maps™ Street View. These landmarks were 3D models of various objects that are commonly observed throughout a city, such as

¹The mean number of intersections crossed at encoding during passive exploration was 12.0, guided was 12.1, and active was 9.7. There were no significant differences between the number of intersections traversed during each exploration type. Importantly, the number of intersections traversed at encoding for each condition did not correlate significantly with route memory performance (Active: $r(48) = -.09$, $p = .515$; Passive: $r(48) = .08$, $p = .570$; Guided: $r(48) = .14$, $p = .347$).

benches, trees, water fountains, bus stops, and traffic lights, downloaded from the free-to-use online source, Sketchfab (sketchfab.com). Finally, the velocity at which participants moved in VR was set at 8ms/sec (analogous to a vehicle going approximately 30 km/hr) within each exploration of an environment.

Measures. Calculation of route overlap as a measure of route memory: The primary dependent variable of interest was the accuracy in reproducing the same route at retrieval that had been travelled during encoding of environments. To obtain this measure of spatial memory performance, the deviation in distance between the routes travelled by each participant at encoding and retrieval, for each of the 12 environments was calculated to produce a deviation distance measure². That is, for every environment, I collected 40 pairs of X, Y coordinates every second, during both initial exploration (encoding) and during retrieval, reflecting a participant’s position in an environment. Using the *Pythagorean theorem*, the Euclidean distance was calculated [$d = \sqrt{(x^2-x^1)^2 + (y^2-y^1)^2}$] between each of the 40 X, Y coordinates from encoding and retrieval (Liberti et al., 2014). I then calculated the average distance (d) value to obtain the mean deviation distance between Encoding and Retrieval for each environment, explored by a participant. A higher value signified that there was greater deviation between the paths making up encoding and retrieval, hence, poorer memory for the route travelled at encoding (see Figure 1, Panel A, for perfect route overlap between encoding and retrieval; see Figure 1, Panel B, for paths representing significant deviation). Finally, I computed the mean route overlap across the four environments in each of the three conditions to obtain a single route overlap value that was the most representative of route memory following passive, guided, and active exploration.

Individual difference measures administered post VR-immersion: Spatial orientation ability of participants was evaluated with the *Santa Barbara Sense-of-Direction (SBSODS)* scale (Hegarty et al., 2005). Visuospatial ability was assessed to later determine whether inherent visuospatial skills influenced route memory performance, beyond our experimental manipulation. Each participant rated their endorsement of 15 statements about spatial orientation in everyday life, such as “I am good at giving directions”, indicating whether they strongly agreed or disagreed, using a 7-point Likert-scale. After reverse scoring the items, the responses were summed and divided by 15 to derive an average score between 1–7. Participants then rated their motivation and preference to explore each condition (Passive, Active, and Guided), on a 7-point Likert-scale, with increasing numbers reflecting greater motivation or preference (e.g., “please rate your motivation to explore environments in VR during active exploration”; “Please rate your preference to explore environments in VR during active exploration”). I also measured simulator sickness using the *Simulator*

²Mean deviation distance was computed for each environment explored (12 environments in total) separately for each condition, i.e. 4 passive, 4 guided, 4 active environments, for each participant.

Sickness Questionnaire (SSQ; Kennedy et al., 1993) to evaluate oculomotor discomfort, disorientation, nausea, and fatigue experienced as a result of VR exposure. We scored this questionnaire by assigning each question a value based on the response. Each “None” response received a score of 0, each “Slight” response received a score of 1, each “Moderate” response received a score of 2, and each “Severe” response received a score of 3. Based on a large sample of *SSQ* data gathered from military pilots, it is suggested that total scores can be associated with negligible (> 5), minimal ($5 - 10$), significant ($10 - 15$), and concerning ($15 - 20$) symptoms (Kennedy et al., 1993). Finally, we administered the *Igroup Presence Questionnaire (IPQ)* to determine the extent to which participants felt present while exploring the VR environments (Schubert et al., 2001). Participants were instructed to rate each statement (e.g., ‘In the computer-generated world, I had a sense of being there’, I felt present in the virtual space’) from a scale of 1 (not at all) to 7 (very much).

Figure 1. Panel A: Example of paths travelled in one of the virtual environments at encoding and retrieval, showing perfect route overlap (good memory for route travelled at encoding).

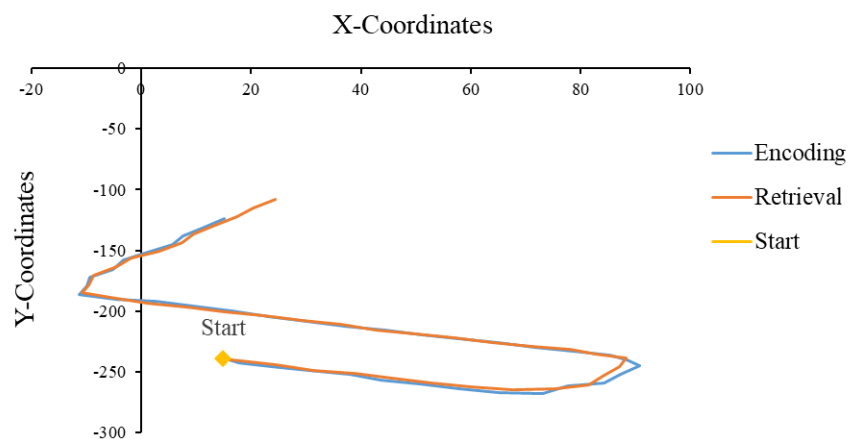
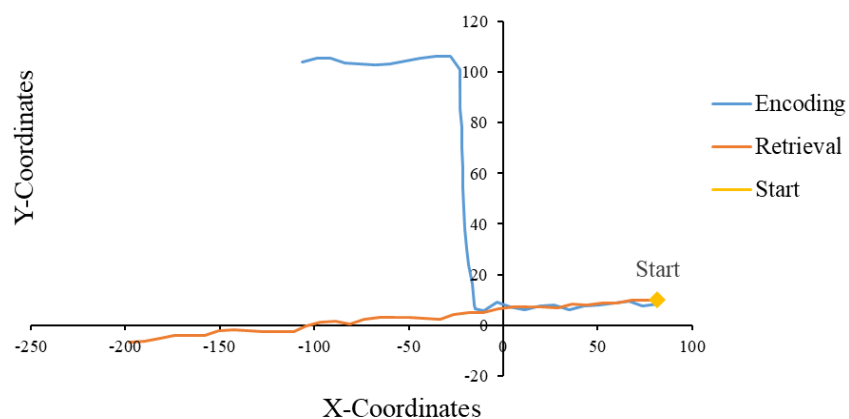


Figure 1. Panel B: Example of paths travelled in one of the virtual environments at encoding and retrieval, showing significant path deviation (poor memory for route travelled at encoding).



Procedure. Throughout the entire VR experiment, participants were seated in a comfortable swivel chair that could turn a full 360°, placed in the center of a testing room. Following verbal instructions on how to use the VR headset, participants completed a practice phase with the VR equipment, designed to help them learn how to use the VR controllers to move within the virtual space. A single handheld VR controller was sufficient to navigate in the environment. To move forward, participants were instructed to press the Trackpad Button of the controller. To change their direction, participants had to rotate their head in the desired direction, as well as physically rotate in the spinning chair with their legs, while pressing the Trigger button on the VR controller, pointed in the direction of travel. I advised participants to take as much time as needed in the training phase in order to become comfortable with the environment. Immediately following the training phase, the experimental session began.

There were two main phases for each of the 12 environments: A study/encoding phase (40 secs), and then a retrieval phase (40 secs) which followed immediately, in which participants reproduced the exact route taken at encoding. During the study phase (i.e., the route of the path taken at encoding), participants explored each of the 12 environments within VR in one of three conditions: Passive, Guided, and Active. Condition was manipulated within-subject, with condition and order counterbalanced across participants.

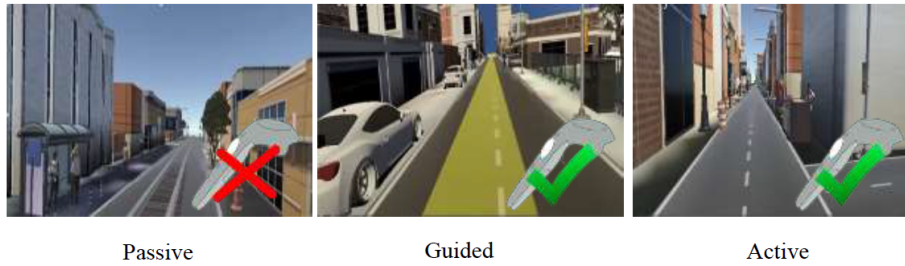
The passive condition was created by recording 360-degree videos of a pre-defined path for each environment. Therefore, the path observed by participants in the passive condition differed to the paths travelled in the guided and active conditions. That is, I did not yoke the passive condition trials to a route travelled in the active or guided conditions. Participants observed the videos within VR to simulate the act of moving inside a vehicle from a passenger’s seat. During passive viewing (see Figure 2), participants were provided with the following instructions: “You will passively explore this environment. During passive exploration, you will experience a tour of the environment leading you to a gold star. You will be able to move your headset, but will have no control over the movement of your hand-held controllers”. To reiterate, participants did not exert motor control for movement, nor decide the path of travel.

The guided condition was created using Mapbox Directions API to automatically generate the optimal path between two waypoints according to path data. Specifically, one end of the waypoint was attached to a fixed location (the gold star), while the other waypoint was attached to the participant so that the path could be updated in real time. This path was colored in Yellow (see Figure 2) and overlaid onto the travelled path so that it was highly visible to participants. During guided exploration, participants received the following instructions “You will be guided during exploration of this environment. During guided exploration, you will follow a yellow-line directing you to a gold star”. Simply put,

during the guided exploration, participants exerted motor control using the VR controllers (along with head and body rotation) to move forward and follow the yellow line directing them to their end-point, but did not decide the path of travel.

During active exploration (see Figure 2), participants were free to choose the route they travelled to find a gold star. That is, participants exerted motor control using the VR controllers, and also decided the path of travel, thus, engaging both motor and decision-making processes. Therefore, the paths travelled in the guided and active conditions differed as the former path was experimentally controlled, while the latter was chosen by the participant. Prior to beginning each new exploration, an instruction appeared on the screen indicating the condition. Immediately after encoding (40 secs) a given environment, participants were placed back at the same starting position, and asked to reproduce (move themselves) along the route they had taken during initial exploration (encoding).

Figure 2. From left to right: passive, guided (movement was controlled via the handheld controller), and active (movement was controlled via the handheld controller) navigation conditions.



Each participant explored all 12 environments. Encoding conditions were blocked by type (4 environments of Passive, 4 environments of Guided, and 4 environments of Active). The order of the three condition blocks (Passive, Guided, and Active) was counterbalanced across participants. The total time spent in VR was approximately thirty minutes (including a break to reduce VR fatigue, before starting a new condition). After completion of the experiment in VR, the researcher administered the scales.

2.3 Results

2.3.1 Route Overlap Memory Performance

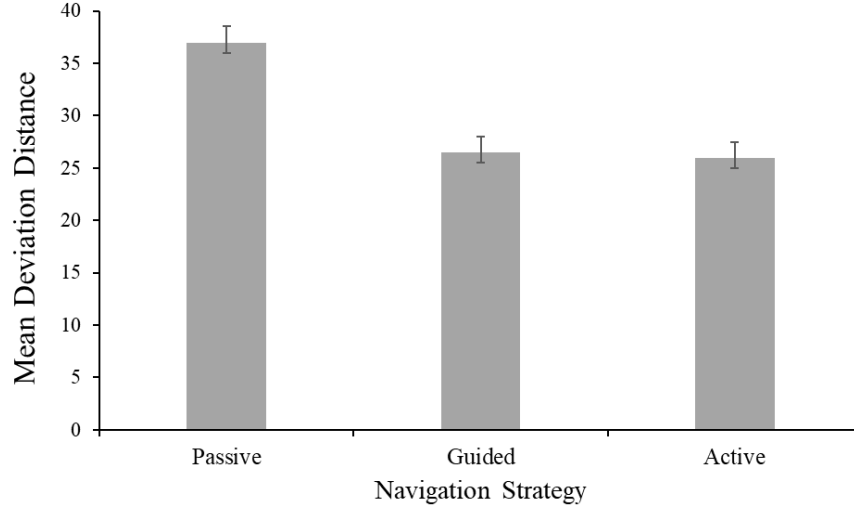
I conducted a one-way repeated measures ANOVA (within-subject variable was Navigation Condition, Passive, Guided, and Active) examining Route Overlap score as the dependent variable³. I observed a significant effect of Navigation Condition on Route Overlap Memory score, $F(1.50, 73.37) = 5.25$, $MSE = 490.29$, $p = .013$, $\eta_p^2 = 0.10$ (see Figure 3 for means)⁴. I then conducted paired sample t-tests to compare Route Overlap score in each of the three Navigation Conditions (Passive, Guided, and Active). Passive exploration resulted in the highest mean deviation in route overlap accuracy relative to Guided and Active Navigation Conditions, $t(49) = 2.53$, $p = .015$, $BF_{10} = 2.72$, $d = 0.36$, 95% CI [0.07, 0.64], and $t(49) = 2.43$, $p = .019$, $BF_{10} = 2.19$, $d = 0.34$, 95% CI [0.06, 0.63], respectively. There were no significant differences between Active and Guided exploration on Route Overlap accuracy, $t(49) = 0.20$, $p = .841$, $BF_{01} = 6.38$, $d = 0.03$, 95% CI [-0.25, 0.31]⁵.

³In addition to route overlap, I also measured the number of stops made at encoding and retrieval for all three navigation conditions. I did not observe any significant correlations between route overlap score and this metric ($p > .05$). I, however, found a significant negative correlation between distance travelled at encoding and route memory in the Active condition, such that, as distance travelled increased, the deviation in route memory performance decreased (i.e., better memory; $r(48) = -.37$, $p = .008$). No such significant relation was found for Guided or Passive navigation.

⁴Mauchly's test indicated that the assumption of sphericity had been violated ($p < .05$) thus; a Greenhouse-Geisser correction was applied.

⁵Bayes factors were calculated using the Bayes-Factor package for R, enlisting a default Jeffreys-Zellner-Siow (JZS) prior with a Cauchy distribution ($center = 0$, $r = 0.707$). This package compares the fit of various linear models. In the present case, Bayes factors for the alternative (BF_{10}) are in comparison to null models with subject-level random error. Bayes factor interpretations follow the conventions of Lee and Wagenmakers (2013). Bayes factors in favor of the alternative (BF_{10}) or null (BF_{01}) models are presented in accordance with each preceding report of null hypothesis significance testing analyses (i.e., based on a $p < .05$ criterion). A $BF_{10} > 1$ is interpreted as evidence in favour of the alternative hypothesis, while $BF_{01} > 1$ is interpreted as evidence in favour of the null.

Figure 3. Route overlap (measured by deviation distance between path travelled at encoding and retrieval) score across Passive, Guided, and Active conditions.



Note. Higher the score on the deviation distance, poorer the memory for routes travelled at encoding. Error bars reflect the standard error of the means.

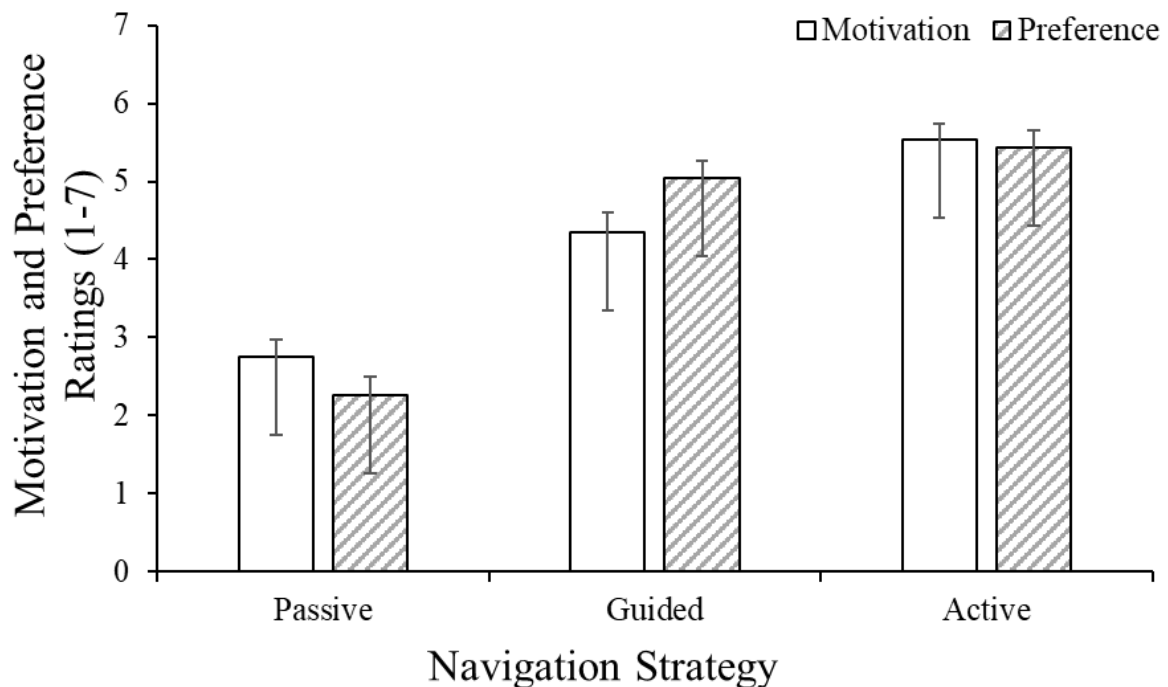
2.3.2 Difference in Self-reported Levels of Motivation and Preference to Explore

I conducted one-way repeated measure ANOVAs to detect significant differences in motivation and in preference rating. As predicted, I observed a significant effect of Navigation Condition on self-reported motivation $F(2, 98) = 45.90$, $MSE = 2.15$, $p < .001$, $\eta_p^2 = 0.48$. Participants reported greater motivation to explore environments under Active and Guided Navigation Conditions (see Figure 4 for means) than Passive, $t(49) = 9.56$, $p < .001$, $BF_{10} = 9.57$, $d = 1.35$, 95% CI [0.96, 1.73], and $t(49) = 5.72$, $p < .001$, $BF_{10} = 2.487^{e4}$, $d = 0.81$, 95% CI [0.49, 1.13], respectively. Notably, participants endorsed Active Navigation as evoking greater motivation for exploration, relative to Guided, $t(49) = 3.92$, $p < .001$, $BF_{10} = 90.31$, $d = 0.55$, 95% CI [0.25, 0.85].

Using preference scores as the dependent variable we again observed a significant main effect of Navigation Condition, $F(2, 98) = 49.00$, $MSE = 3.06$, $p < .001$, $\eta_p^2 = 0.40$.

Specifically, participants preferred to explore environments under Active and Guided navigation strategies (see Figure 4 for means) significantly more than in Passive, $t(49) = 8.19$, $p < .001$, $BF_{10} = 1.03$, $d = 1.16$, 95% CI [0.80, 1.51], and $t(49) = 8.90$, $p < .001$, $BF_{10} = 1.12$, $d = 1.26$, 95% CI [0.88, 1.63], respectively. There were no significant differences in preference rating between Active and Guided Navigation Strategies, $t(49) = 1.16$, $p = .252$, $BF_{01} = 3.46$, $d = 0.16$, 95% CI [-0.12, 0.44]. I did not, however, find any significant correlations between motivation and preference scores and route overlap in any one of the three navigation conditions ($p > .05$).

Figure 4. Mean motivation and preference scores for Passive, Guided, and Active conditions.



Note. Error bars reflect the standard error of the means.

2.3.3 Correlation Between Route Overlap Score and Individual Difference Measures

Given my goal of determining whether route memory performance in each of the navigation conditions was related to various individual difference factors pertaining to spatial navigation (measured by *SBSODS*; $M = 4.08$, $SD = 1.09$), sense of presence in VR (measured by *IPQ*; $M = 3.81$, $SD = 0.47$), and simulator sickness (measured by *SSQ*; $M = 11.60$, $SD = 8.65$), I ran a series of Pearson correlations. I did not observe any significant associations between route overlap (in Passive, Guided, and Active explorations) and inherent spatial navigation abilities of participants, VR sickness, and sense of presence ($p > .05$).

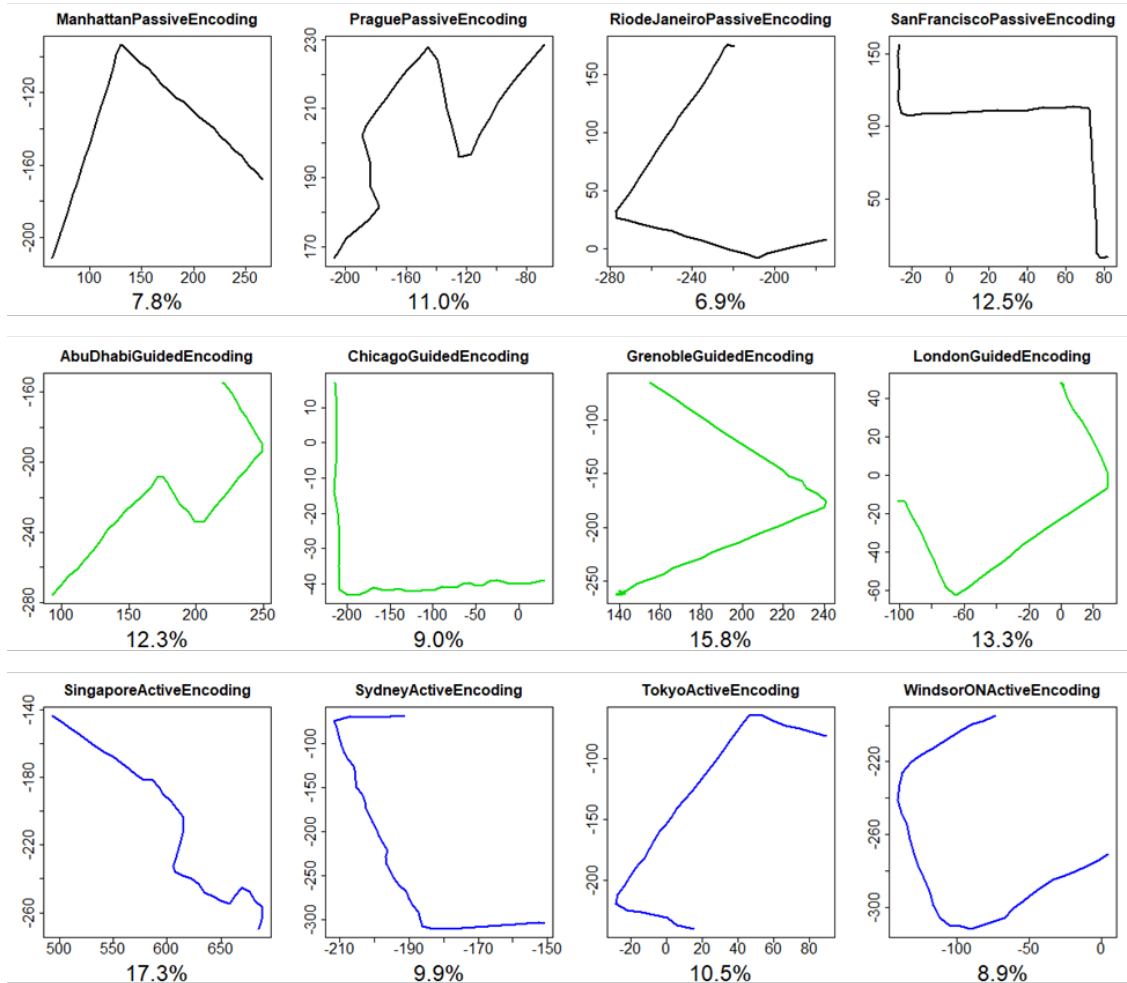
2.3.4 Assessment of Path Complexity Across the Three Exploration Conditions

I also considered whether differences in path taken across the three exploration conditions influenced subsequent memory for the route travelled. I applied an angle-based measure (see Appendix for a detailed description of the equation) of path complexity to each participant's encoding phase of each environment. That is, I recorded each participant's position within each environment, at each time-point during their 40-second exploration. I then derived displacement vectors between positions at each consecutive time-point. Next, I calculated the angle between each pair of consecutive displacement vectors and normalized these angles to represent a complexity score between 0 and 1, such that a 0-degree turn (straight path) has a complexity of 0, and a 90 degree turn or greater has a complexity of 1. Finally, I tabulated the average of the individual turn complexity scores to determine the overall path complexity in percentage, for environments by condition. Figure 5 shows path complexity percentages for all twelve environments explored by a participant, with those explored in the Active condition shown in blue, in the Guided condition shown in green, and in the Passive condition shown in black.

I conducted a one-way repeated measures ANOVA comparing the percentage of path complexity across the three Encoding conditions (active, guided, and passive). I found a significant main effect of path complexity, $F(1.09, 53.18) = 6.64$, $MSE = 0.01$, $p = .011$, $\eta_p^2 = 0.12$. Bonferroni corrected t-tests revealed that the path explored during the active encoding condition ($M = 13\%$; $SD = 0.13$) was significantly more complex than that of the passive condition ($M = 7\%$; $SD = 0.01$), $t(49) = 3.64$, $p = .001$, $d = 0.72$, 95% CI [0.21, 1.22]. No other significant differences emerged. Correlational analyses also revealed no significant relationship between active, guided, and passive path complexity,

and route memory performance ($p > .05$). In light of these findings, I do not believe that any variations in the path taken could have significantly influenced route learning.

Figure 5. Sample of a participant's path complexity and percentage (shown underneath) of each environment explored, with Passive condition shown in black, Guided condition in green and Active condition in blue.



2.4 Discussion

Past research suggests that active relative to passive exploration of an environment enhances memory. Past work also suggests that active navigation requires engaging both cognitive (mental manipulation of spatial information, allocation of attention, and decision-making) and physical (motor control for locomotion, proprioceptive, and vestibular sensory information) components (Chrastil & Warren, 2012). It is unclear, however, whether following directions provided by an external aid helps or hinders later route memory, as this type of guided navigation retains volitional control of movement, but removes decision-making (i.e., self-directed choice).

In the current study, I created encoding conditions that differentially required decision-making and motor control, and compared the influence of these navigation conditions on memory for the route travelled. Navigation condition during encoding was manipulated within-subjects, and required either actively self-initiating decision-making about the route of travel, or simply following a visually guided route; in both conditions, volitional control of movements occurred using hand-held controllers that engaged head, body, and arm movements to advance through streets. In a third encoding condition, participants passively viewed pre-determined routes within VR, requiring no decision-making and motoric engagement. Of particular interest, in the ‘guided navigation’ condition, I examined whether motor control alone, in the absence of decision-making, would limit acquisition of route memory and render route memory, similar to that following Passive navigation.

Relative to the passive condition, both actively self-initiated and visually-guided navigation similarly and significantly benefited the accuracy of route overlap between path travelled during exploration and retrieval. Results revealed that visual navigational guidance during an exploration phase does not impair later retrieval of routes travelled. I suggest that motor engagement involving head, body, and arm movements during encoding, more so than decision-making about which route to travel, influences subsequent route memory.

Moreover, I found that participants rated their preference to explore environments under Active and Guided navigation similarly, and both more so than the environments in the Passive condition. In terms of motivation, participants reported the greatest motivation to explore environments under active, followed by guided and passive navigation conditions. These findings are in line with prior work showing that elevated states of curiosity evoked by exploratory activities or stimuli that are surprising, novel, and of intermediate complexity, foster both spontaneous exploration and active learning in children, as well as younger and older adults (Gruber et al., 2014; Sakaki et al., 2018). It is plausible that participants

regarded both active and guided navigation to be activities of intermediate complexity and novel, as these navigation conditions required active exploration in VR, whereas passive exploration only required the observation of a pre-recorded path in VR. Although I found active and guided navigation to yield better memory performance, relative to passive, I did not detect a significant correlation between route overlap in these conditions and motivation and preference reporting. I also did not detect any significant associations between route overlap and inherent spatial navigational abilities of participants, VR sickness, and sense of presence. Future work could examine whether a relationship might emerge by gathering more precise moment-by-moment measurements of motivation and preference during the exploration phase. Another approach would be to experimentally manipulate participant’ level of motivation and preference by asking them to explore an environment that is personally salient, or that is void of landmarks and simple in environment configuration.

2.4.1 Limitations

In the current study, motor control by the participant entailed head and body rotation, while seated in a chair that could turn a full 360°. It is true that sitting limits sensory and motor cues about one’s location in space when exploring a new environment, relative to walking. However, my research paradigm still allowed for participants to engage sufficient motor command to dictate the path of travel (i.e., motor signals to enable head and body rotation, and pressing of trackpad on the VR controller) and utilize vestibular information received from head rotation (see Chrastil and Warren, 2012 for review; Von Stülpnagel & Steffens, 2012). Nonetheless, future studies could allow for greater motor engagement by having participants walk while immersed in VR to better simulate the inertial cues (i.e., cues that provide information about linear and angular acceleration) evoked when exploring new surroundings (Waller et al., 2003).

Another limitation of the current study is that I did not control for the number of intersections in each map, as cities were created to resemble real-world map configuration. For example, past work revealed that pausing near intersections during active encoding was related to, and predictive of, route overlap accuracy, illuminating another cognitive component that contributes to the benefit of active navigation (Meade et al., 2019). Future studies could control for the number of intersections across environments and examine eye movements at critical intersections to examine the influence of route planning on later memory (Zhu et al., 2022). Relatedly, I did not equate the routes travelled in the passive, guided, and active conditions during the encoding phase. That is, I did not use a recording of the “active” route to generate the “guided” and “passive” routes. However, my analysis

of path complexity revealed that the path explored during the active encoding condition was significantly more complex than that of the passive condition. No other significant differences emerged. However, because I did not find a significant correlation between overall path complexity and route memory performance for any of the conditions, I do not believe this undermines my findings.

2.4.2 Conclusion

The findings of this chapter suggest that integrated self-generated motor activity at encoding is critical to benefit route memory. Given this, relying on an external GPS device for route guidance may not dampen our memory for those particular routes, as long as the motor system is engaged during initial encoding. These findings have implications for the way in which GPS navigational aids are currently viewed by the public and by the scientific community. Specifically, the results of the current study emphasize the need to precisely define and measure distinct measures of spatial navigation (i.e., route memory, survey knowledge, landmark recognition), and to determine the way in which GPS uniquely influences each measure.

Chapter 3

The Necessity of Motoric Engagement in Enhancing Route Memory

3.1 Introduction

Prior work shows that people differ greatly in their navigational proficiency (Chrastil & Warren, 2012 for review; Weisberg & Newcombe, 2016). For example, some people can use a map to form a Birds-eye view of spatial routes, which enables them to integrate familiar and novel paths to assist navigation (Gaunet et al., 2001). Other people, however, are more reliant on navigational apps such as Google MapsTM, which provide turn-by-turn instructions, to help guide them to their destination faster (Dahmani & Bohbot, 2020). When examining memory for routes, and the spatial layout of an environment, several studies have consistently shown that active navigation during encoding results in better performance, relative to a passive tour of an environment (see Chrastil & Warren, 2012 for review; Maguire et al., 2006). Active encoding consists of both cognitive (mental manipulation of spatial information, allocation of attention, and decision-making) and physical (motor control for locomotion, proprioceptive, and vestibular sensory information) components that are believed to be combined to create a multi-modal representation of the path travelled (Chrastil & Warren, 2012). Passive encoding, in which the person simply views a route without motoric engagement or decision-making about where to turn leads to consistently poorer retention. That is, acquisition of spatial knowledge is limited when individuals passively view routes, as in the case of a passenger who is simply observing

a path, relative to a driver who initiates their own decisions about where to explore and how to arrive at a location (Chrastil & Warren, 2012). Some suggest that engaging in decision-making during encoding is the key factor benefitting later memory (see Chrastil & Warren, 2012 for review; Weisberg & Newcombe, 2016). However, it remains uncertain whether it is the lack of decision-making that accounts for poorer memory following passive viewing, or lack of motoric engagement.

In Experiment 1, I found that removing decision-making during Guided navigation did not impede memory for routes travelled relative to Active exploration. If volitional motor engagement is truly the underlying mechanism for successful route knowledge, then altering the level of motor control required at encoding should vary memory performance. To this end, in Experiment 2, I examined whether altering the level of motor engagement at the time of encoding modulates memory for routes travelled. That is, I manipulated the need for decision-making during encoding of a new route within virtual reality (VR), as well as the motoric demands for movement, to determine their relative influences on memory. Movement was initiated either within Desktop viewing of environments (using a QWERTY keyboard for movement and mouse control for rotational viewing) or within a VR headset using a VR-compatible steering wheel that allowed for greater motoric involvement. My goal here was to determine the degree to which motoric engagement is necessary to enhance memory for routes.

3.1.1 Method of Implementation: Desktop Versus Headset-based Viewing Within VR

Recent advancements in VR technology have introduced a new variable to consider when assessing spatial memory: the type of VR device used to interact with the virtual environment. The type of VR apparatus determines not only the display modality (on a computer monitor in Desktop viewing, or 360-degree integrated viewing with head-mounted VR), but also the level of motor engagement with the virtual environment. Simply put, not only is field of view (FOV) different in these implementations but so is the motoric interaction evoked by the system (Wilson and Soranzo, 2015; Jerald & Marks, 2016; Roettl and Terlutter, 2018). For example, in Desktop VR, participants explore virtual environments primarily using a keyboard to move through the environment, and a mouse to control the camera view (i.e., to observe around an environment). On the other hand, exploring a virtual environment using headset-based VR is quite different. Movement is typically controlled with VR paddles, or in the case of the current study, using a VR-compatible steering wheel to control the direction of movement (e.g., turning the wheel changes the

direction in which the virtual environment moves), and pedals to control acceleration and deceleration. Critically, the level of motor engagement required by the latter VR system generates inertial cues about one’s movement and position in space that are then relayed to the brain (Murcia-López & Steed, 2016; Waller & Nadel, 2013). Inertial cues can play an important role in spatial navigation by providing information about movement and orientation relative to one’s body (Jerald & Marks, 2016; Loomis & Knapp., 2003). These cues include proprioceptive feedback from sensory receptors in muscles and joints, vestibular information from the inner ear that detects head position and motion, and accelerative cues that indicate changes in velocity (Jerald & Marks, 2016). Self-motion cues integrate these inputs to help individuals perceive their trajectory and orientation in space. When combined with visual cues, these inertial cues are believed to enhance spatial awareness and navigation capabilities (Jerald & Marks, 2016). In VR, replicating realistic inertial feedback can improve immersion and accuracy, demonstrating the importance of these cues in both real and virtual environments for navigation.

When examining the role of spatial navigation using different VR implementations, it is also essential to consider the interactive influence of one’s sense of presence and immersion. Presence fosters a sense of “being there”, which not only enhances the encoding of spatial information by grounding the experience in a perceived real-world context, but may also increase the attention devoted to the virtual environment (Makowski et al., 2017). Further, it is hypothesized that attention mediates the positive benefits of presence on memory (Smith & Mulligan, 2021; Makowski et al., 2017). It is reasonable to presume that under headset-based viewing, the level of presence evoked by a virtual environment would be higher to that simulated under Desktop viewing. Therefore, in the current work I measured self-rated presence, post-VR immersion, to determine its influence on subsequent memory performance.

Past research has also shown that spatial learning is most effective in immersive conditions and that presence could mediate the effect of immersion on the acquisition of spatial knowledge within virtual environments (Parong et al., 2020). For instance, Cadet and Chainay (2020) found that using a more immersive Headset-VR device (similar to the one used in the current study) resulted in better memory performance and heightened presence compared to Desktop-VR implementation. Researchers also suggest that immersion plays a critical role in enhancing spatial memory by engaging multiple sensory and motor modalities (Smith & Mulligan, 2021; Makowski et al., 2017; Bampouni et al., 2024). In other words, non-immersive devices are believed to restrict the full motor and sensory experience that can be evoked by active navigation tasks. Conversely, immersive Headset-VR systems that enable motor control and head movement are suggested to provide bodily-based (idiothetic) motor cues, which are essential for spatial memories, like route knowledge, which

rely on an egocentric frame of reference¹.

3.1.2 Current Study

In this study, I sought to examine whether a change to the method of implementation of environments within VR (Desktop viewing versus Headset-based VR with steering-wheel compatibility) would alter memory for routes. In the experiment detailed in Chapter 2, I created encoding conditions that differentially required decision-making and motor control, and compared the influence of these navigation types on memory for the route travelled (Sivashankar et al., 2024). Navigation type during encoding was manipulated within-subjects and required either actively self-initiating decision-making about the route of travel (Active navigation) or simply following a visually guided pre-determined route (Guided navigation). In both conditions, volitional control of movements occurred using hand-held controllers that engaged head, body, and arm movements to advance through streets (using an HTC-VIVE VR system). In a third navigation type, participants passively viewed set routes within VR (Passive navigation) without the need to initiate decisions about the route of travel nor engage in motoric exploration. Findings from Chapter 2 indicated that both actively self-initiated and visually-guided navigation conditions significantly improved the accuracy of route memory compared to the passive condition. This suggests that limiting decision-making at encoding does not hinder route memory performance. Instead, I argued that motor engagement, involving head, body, and arm movements during encoding, plays a more pivotal role in enhancing subsequent route memory than decision-making (Sivashankar et al., 2024). In the current Chapter, my aim was to determine whether my findings reported in Chapter 2 would replicate when varying the level of motor engagement allowed by different VR implementations: Desktop-VR and Headset-VR. Such an investigation is important not only for understanding the cognitive mechanisms underlying spatial memory, but also to offer insight into the best protocols using VR technologies, to examine human navigation.

As in Chapter 2, a second goal of mine was to document the relationship between individual differences in navigation abilities, preferences and motivations for various encoding types, and to determine how trait-level curiosity influences memory performance. To this end, I asked participants to complete a questionnaire to assess their everyday navigation skills using the *Santa Barbara Sense of Direction Scale (SBSODS)*; Hegarty et al., 2006).

¹An egocentric frame of reference is a spatial representation system where locations and orientations are defined relative to the individual's own body, encompassing coordinates linked to the eyes, head, and torso (Ruggiero et al. 2009).

Further, I measured variations in self-reported motivation and preference for each navigation strategy (Passive, Guided, and Active) and examined whether this influenced route memory.

In Experiment 2, participants also completed the *Five-Dimensional Curiosity Scale* (5DC). This questionnaire assesses participants' inherent qualities of curiosity related to joyous exploration, deprivation sensitivity, stress tolerance, social curiosity, and thrill seeking (Litman, 2005). As described in Chapter 2, I demonstrated a significant link between curiosity and route memory performance in children (Sivashankar et al., 2024). In this Chapter, I aimed to explore whether individual differences in the emotional states elicited by curiosity, such as feelings of joy versus fear, might affect route memory. For example, past research suggests that the emotional states underlying curiosity can differentially shape memory. That is, curiosity paired with positive emotions such as interest or joy tends to enhance hippocampal engagement and exploratory behavior, leading to better route encoding and retrieval. In contrast, curiosity mixed with fear or anxiety can narrow attention, increase avoidance, and disrupt the integration of spatial cues, ultimately impairing route memory. These divergent effects highlight how the emotional tone accompanying curiosity can either facilitate or hinder navigation performance (Litman, 2005; Sauzéon et al., 2016). Such an examination has broader implications for understanding the influence of curiosity on memory. Lastly, I measured simulator sickness (Kennedy et al., 1993; Simulator Sickness Questionnaire) and participants' sense of presence in VR (Schubert et al., 2001; Igroup Presence Questionnaire) to assess the perceived realism of the virtual environments, and to explore whether these aspects directly influenced or mediated memory performance.

3.2 Methods

Participants. In Experiment 2, I detected a significant main effect of navigation condition in a one-way repeated measures design, using a sample of 50 participants (Sivashankar et al., 2024). Given that the current work extends my prior research and aims to detect a similar effect of encoding strategy on route memory, but using different VR apparatuses, I sought to maintain a comparable sample size for this study. This approach ensured that the sample size was both theoretically grounded and empirically informed. In the present study, 54 undergraduate students (16 males, 38 females; $M_{age} = 22.0$ years, $SD = 2.20$) from the University of Waterloo were recruited on a volunteer basis to be in the Desktop-VR group. Another independent sample of 54 undergraduates (16 males, 38 females; $M_{age} = 24.0$ years, $SD = 3.20$) were recruited to be in the Headset-based VR

group. The Research Ethics Committee approved all study procedures. Written informed consent was obtained from all participants prior to experimentation. Data collection for the Desktop-VR group began in January of 2023 and was completed by July of 2023. Data collection for the Headset-VR group began in September of 2023 and was completed by February of 2024. See Table 1 for descriptive statistics on individual difference measures from participants in each group.

Table 1.*Individual difference measures from participants in the Desktop-VR and Headset-VR Groups*

Group and Measures	Mean (SD)
Desktop-VR Group	
<i>Santa Barbara Sense of Direction Scale (SBSODS)</i>	4.23 (0.88)
Headset based-VR Group	
<i>Santa Barbara Sense of Direction Scale (SBSODS)</i>	4.14 (1.04)
<i>Simulator Sickness Questionnaire (SSQ)</i>	6.17 (5.08)
<i>I-Group Presence Questionnaire (IPQ):</i>	
Presence	4.72 (1.51)
Spatial presence	4.32 (0.71)
Involvement	3.91 (0.47)
Experience realism	2.85 (1.42)
Total mean IPQ	3.75 (0.57)
<i>Five-Dimensional Curiosity Scale (5DC):</i>	
Joyous exploration	5.02 (1.23)
Deprivation sensitivity	4.37 (1.42)
Stress tolerance	4.54 (1.41)
Social curiosity	5.45 (1.04)
Thrill seeking	4.41 (3.90)

Note. For the Desktop-VR group, scales assessing simulator sickness, presence, and curiosity were not administered.

Materials. VR-Application: A computer-run VR application was designed on the 3D Unity © engine (ver. 2019.4.4f1; see specifications on <https://www.vive.com/ca/>), using the software Mapbox (<https://www.mapbox.com/>). Environments in my VR program were chosen to be equivalent in environment sizes. Google Maps Street™ View was then used to decide specific streets within an environment to include in the VR program. Environments were all topographically (i.e., structural organization of the environment) similar, with an average area of 100,000 square meters (measured using Google Earth™ polygon tracing) with a minimum of 4 and a maximum of 20 intersections (point at which two or more roads converged). Since I created the environments to simulate how the cities appear in the real world, some environments contained a greater number of intersections than others. I believe this is an advantage to our study because real-world cities naturally vary in structural topography. The diversity in layout within our map allowed us to more realistically assess the relationship between key factors known to impact navigation, such as intersections (Moser et al., 2008). I then modified the specifications of the environments to allow integration with Desktop-VR and Headset-based VR systems. The VR application included 12 virtual environments created by entering the longitudinal and latitudinal coordinates of various cities around the world (e.g., Abu Dhabi, Chicago, Grenoble, London, Manhattan, Prague, Rio de Janeiro, San Francisco, Singapore, Sydney, Tokyo, Windsor) into the Mapbox Environments SDK for Unity © engine². The speed of travel during all encoding conditions was controlled at 8 m/s.

I replaced the VR controls with suitable analogues for the desktop version of the experiment: The SteamVR plugin, which enabled the use of the VR headset as the in-game player camera, was replaced with a static camera attached to a player object in Unity. The controls for the viewing angle and direction of the camera were shifted to the computer mouse's position and movement inputs to compensate for the removal of head rotation. Further, the player's movement was remapped from VR trackpad controls to the WASD keyboard keys (i.e., the four directional arrow keys, placed on the left side of the keyboard to allow the right hand to more comfortably use the mouse).

I then adapted the Desktop-VR version of the experiment to function with the Headset-based VR group, with movement controlled using a VR-compatible steering wheel. To do this, I again re-mapped the input controls onto a different hardware system. The ability to turn left and right was assigned to a steering wheel using the [Input System Unity plugin Version 1.6.1] Unity plugin, with the degree of wheel rotation modulating the magnitude of

²I collected data on meters traveled as a proxy for distance covered, under the assumption that traveling faster would likely result in covering a greater distance. Correlation analysis did not reveal a significant association between meters traveled during encoding, and route memory performance, in either group, $r(52) = .22$, $p = .467$ (Desktop-VR) and , $r(52) = .26$, $p = .423$ (Headset-VR).

the turn. Moving forward was assigned to the accelerator, while the brake pedal was used to pause at any given time during the exploration phase. Finally, as mentioned above, the velocity at which participants moved within each exploration of an environment was set at 8 m/sec (analogous to a vehicle going approximately 30 km/hr). Each participant explored all 12 environments. Encoding/Navigation strategy was blocked by type (4 Passive, 4 Guided, and 4 Active), with order counterbalanced, and presented within-subjects.

Individual Difference Measures Administered Post VR-immersion. Desktop-VR Group: Spatial orientation ability of participants was evaluated with the *Santa Barbara Sense-of-Direction Scale (SBSODS)* (Hegarty et al., 2006). Each participant rated their endorsement of 15 statements about spatial orientation in everyday life, such as “I am good at giving directions”, indicating whether they strongly agreed or disagreed, using a 7-point Likert-scale. After reverse scoring the items, the responses were summed and divided by 15 to derive an average score between 1–7. Participants then rated their motivation and preference to explore each navigation type (Passive, Active, and Guided), on a 7-point Likert-scale, with increasing numbers reflecting greater motivation or preference (e.g., “please rate your motivation to explore environments in VR during active exploration”; “Please rate your preference to explore environments in VR during active exploration”).

Headset-based VR Group: Participants completed the *SBSODS* and rated their motivation and preference to explore each navigation type. I also measured simulator sickness using the *Simulator Sickness Questionnaire (SSQ)* (Kennedy et al., 1993) to evaluate oculomotor discomfort, disorientation, nausea, and fatigue experienced because of VR exposure³. I scored this questionnaire by assigning each question a value based on the response. Each “None” response received a score of 0, each “Slight” response received a score of 1, each “Moderate” response received a score of 2, and each “Severe” response received a score of 3. I then administered the *Igroup Presence Questionnaire (IPQ)* to determine the extent to which participants felt present while exploring the VR environments (Schubert et al., 2001). Participants were instructed to rate each statement (e.g., “In the computer-generated world, I had a sense of being there”, I felt present in the virtual space”) from a scale of 1 (not at all) to 7 (very much). Finally, participants completed the *Five-Dimensional Curiosity Scale (5DC)*. This questionnaire assessed participants’ inherent qualities of curiosity related to joyous exploration, deprivation sensitivity, stress tolerance, social curiosity, and thrill seeking (Litman, 2005).

Measures. Calculation of Route Overlap as a Measure of Route Memory: The primary

³Based on a large sample of SSQ data gathered from military pilots, it is suggested that total scores can be associated with negligible (< 5), minimal (5 – 10), significant (10 – 15), and concerning (15 – 20) symptoms (Kennedy et al., 1993).

dependent variable of interest was accuracy in re-tracing the same route at retrieval that had been travelled during the encoding of each environment. To obtain this measure of spatial memory performance, the deviation in distance between the routes travelled by each participant at encoding and retrieval, for each of the 12 environments was calculated to produce a deviation distance measure⁴. That is, for every map, we collected 40 pairs of X, Y coordinates every second, during both initial exploration (encoding) and during retrieval, reflecting a participant’s position in a map. Using the *Pythagorean theorem*, the Euclidean distance was calculated [$d = \sqrt{(x^2-x^1)^2 + (y^2-y^1)^2}$] between each of the 40 X, Y coordinates from encoding and retrieval (Liberti et al., 2014). I then calculated the average distance (d) value to obtain the mean deviation distance between encoding and retrieval for each map, explored by a participant. A higher value signified that there was greater deviation between the paths making up encoding and retrieval, hence, poorer memory for the route travelled at encoding. Finally, we computed the mean route overlap across the four environments in each of the three conditions to obtain a single route overlap value that was the most representative of route memory following Passive, Guided, and Active explorations.

Procedure. Desktop VR-Group: Participants first completed a practice phase to help them learn which keyboard buttons to use to navigate within the virtual space. Throughout the entire VR experiment, participants were seated in a comfortable chair that could turn a full 360°, placed in the center of a testing room. They were instructed to use the WASD keyboard keys to control movement: the W key was used to move forward, A to turn left, S to move backward, and D to turn right. Further, participants could adjust their camera viewing angle—and, consequently, their forward movement direction—by moving the mouse. I advised participants to take as much time as needed in the training phase to become comfortable with the virtual environment. Immediately following the training phase, the experimental session began. There were two phases for each of the 12 environments: An exploration/ encoding phase (40 secs), followed immediately by a retrieval phase (40 secs), in which participants were asked to re-trace the exact route they had traveled during encoding. Navigation type during encoding was blocked (4 environments using Passive, 4 environments using Guided, and 4 environments using Active navigation), and manipulated within-subject, with order counterbalanced.

The Passive condition was created by recording 360-degree videos showing a set path travelled within each environment. During passive viewing (see Figure 6), participants were provided with the following instructions: “You will passively explore this environment. During passive exploration, you will experience a tour of the environment leading you to a

⁴Mean deviation distance was computed for each map explored (12 environments in total) separately for each condition (i.e., 4 Passive, 4 Guided, 4 Active environments, for each participant).

gold star”. Here, participants did not exert any motor control for movement (no pressing of the keyboard), nor decide the path of travel, but could control their view using the mouse.

The Guided condition was created using Mapbox Directions API to automatically generate the optimal path between two waypoints. One end of the waypoint was attached to a fixed location (the gold star), while the other waypoint was attached to the participant so that the path could be updated in real time. This path was colored in Yellow (see Figure 6) and overlaid onto the road so that it was highly visible to participants. During Guided exploration, participants received the following instructions “You will be guided during exploration of this environment. During guided exploration, you will follow a yellow-line directing you to a gold star”. Simply put, participants only exerted motor control by pressing [W] key to accelerate within the environments, but did not decide the path of travel, as they simply followed the yellow line directing them to their end-point.

During Active exploration (see Figure 6), participants were free to choose the route they travelled to find a gold star. That is, participants exerted motor control via keyboard button press and decided the path of travel, thus engaging both motor and decision-making processes. Before beginning each new exploration, an instruction appeared on the screen indicating the condition type. Immediately after encoding (40 secs) a given environment, participants were placed back at the same starting position and were asked to re-trace (move themselves) along the route they had taken during initial exploration. The total time spent in exploration was approximately thirty minutes. I then administered the scales (*SBSODS*, preference, and motivation).

Figure 6. Display seen in the Desktop-VR group. From left to right: Passive, Guided, and Active Navigation Types.



Headset-VR Group: The procedure was identical to that outlined above, but with movement on Active and Guided trials controlled using a VR-compatible steering wheel (see Figure 7). During these trials, participants directed their gaze and oriented their head, body, and the VR-compatible steering wheel, towards a desired path of travel. That is, both active and guided navigation types required the participant to rotate their head to look towards a desired path (e.g., rotating the head to the left prior to a left turn), along with rotation of their body, and the steering-wheel, to turn left or right at intersections (participants remained seated while they rotated in the swivel chair). In addition, participants had control over acceleration using their foot to depress a metal pedal (see Figure 7).

Figure 7. Display during Headset-based VR. From left to right: Passive, Guided, and Active Navigation Types.



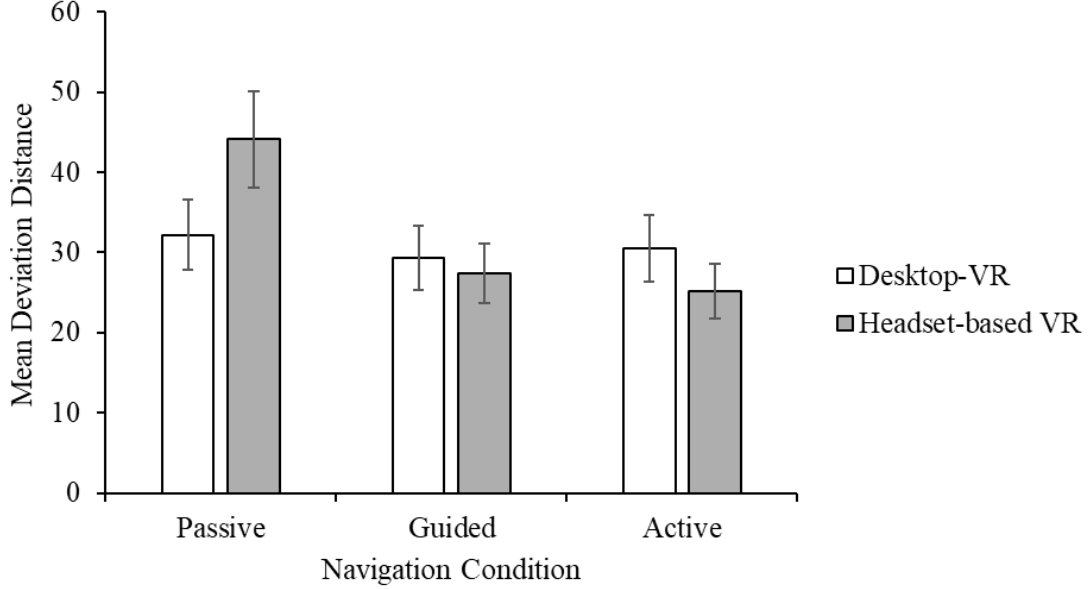
3.3 Results

3.3.1 Route Memory Performance

I conducted a 2 (Group: Desktop-VR vs Headset-VR) X 3 (Navigation Condition: Passive, Guided, and Active) mixed Analysis of Variance (ANOVA), with the first factor being between- and the second factor a within-subject manipulation, on Route Overlap scores. There was a main effect of Navigation Condition, $F(1.61, 170.10) = 14.96$, $MSE = 303.76$, $p < .001$, $\eta_p^2 = 0.12$. Both Active ($M = 27.88$, $SD = 4.53$) and Guided navigation ($M = 28.36$, $SD = 3.56$) improved route memory performance compared to Passive navigation ($M = 38.18$, $SD = 4.78$). There was no difference between Active and Guided performance.

There was no effect of Group (Type of Device), $F(1, 106) = 0.47$, $MSE = 417.07$, $p = .495$, $\eta_p^2 = 0.00$. As predicted, we also observed a significant Group X Navigation Condition interaction (see Figure 8), $F(1.61, 170.10) = 9.32$, $MSE = 303.76$, $p < .001$, $\eta_p^2 = 0.08$. To understand the interaction, we conducted separate one-way ANOVAs for each Group.

Figure 8. Route overlap (measured by deviation distance between path travelled at encoding and retrieval) score in Passive, Guided, and Active conditions.



Note. Lower deviation distance values indicate better memory for routes travelled. Error bars represent the standard error of the means.

Desktop-VR Group. I conducted a one-way repeated measures ANOVA to examine the effect of Navigation Condition on Route Overlap score as the dependent variable. There was no significant effect of Navigation Condition, $F(1.46, 77.41) = 0.32$, $MSE = 485.04$, $p = .658$, $\eta_p^2 = .006$ (see Figure 8 for means).

Headset-VR Group. I conducted another one-way repeated measures ANOVA to examine the effect of Navigation Condition on Route Overlap score as the dependent variable in Headset -VR Group. Here, I observed a significant effect of Navigation Condition on Route Overlap Memory score, $F(2, 108) = 45.22$, $MSE = 130.78$, $p < .001$, $\eta_p^2 = 0.46$ (see Figure 8 for means). I then conducted paired sample t-tests to compare Route Overlap scores across each Condition (Passive, Guided, and Active). Passive exploration resulted in the highest mean deviation in route overlap accuracy relative to Active and Guided Navigation Conditions, $t(53) = 8.21$, $SE = 2.18$, $p < .001$, $BF_{10} = 2.72$, $d = 1.11$, and $t(53) = 7.23$, $SE = 2.18$, $p < .001$, $BF_{10} = 2.19$, $d = 0.98$, respectively. There was no significant difference between Active and Guided exploration on Route Overlap accuracy, $t(53) = -1.01$, $SE = 2.18$, $p = .932$, $BF_{01} = 6.38$, $d = -0.18$.

3.3.2 Self-reported Motivation

I conducted a 2 (Group: Desktop-VR vs Headset-VR) X 3 (Navigation Condition: Passive, Guided, and Active) mixed ANOVA, with the first factor being between- and the second factor a within-subject manipulation, on self-reported Motivation. There was a main effect of Navigation Condition, $F(2, 212) = 16.63$, $MSE = 2.42$, $p < .001$, $\eta_p^2 = 0.14$. That is, motivation was higher in both Active ($M = 5.52$, $SD = 1.48$) and Guided conditions ($M = 5.09$, $SD = 1.57$) relative to Passive ($M = 4.32$, $SD = 1.90$). There was no effect of Group, $F(1, 106) = 1.85$, $MSE = 3.23$, $p = .177$, $\eta_p^2 = 0.02$. There was a significant Navigation Condition X Group interaction (see Table 2 for descriptives), $F(2, 212) = 4.55$, $MSE = 2.42$, $p = .012$, $\eta_p^2 = 0.04$. To understand the interaction, I conducted separate one-way ANOVAs for each Group.

Desktop-VR Group. I conducted one-way repeated-measure. There was a significant effect of Navigation Condition on self-reported Motivation $F(2, 106) = 18.93$, $MSE = 2.47$, $p < .001$, $\eta_p^2 = 0.26$. Participants reported greater motivation to explore environments under Active and Guided (see Table 2 for descriptives) relative to Passive, $t(53) = 5.93$, $SE = 0.31$, $p < .001$, $BF_{10} = 63285.12$, $d = 0.81$, and $t(53) = 4.06$, $SE = 0.29$, $p < .001$, $BF_{10} = 142.97$, $d = 0.55$, respectively⁵. Notably, participants endorsed Active Navigation as eliciting higher motivation for exploration relative to Guided, $t(53) = 2.13$, $SE = 0.31$, $p = .038$, $BF_{10} = 1.18$, $d = 0.29$.

Headset-VR Group. There was no effect of Navigation Condition on self-reported Motivation (see Table 2 for descriptives), $F(2, 106) = 1.93$, $MSE = 2.37$, $p = .151$, $\eta_p^2 = 0.04$.

⁵All t-tests reported in this paper have been Bonferroni-corrected for multiple comparisons.

Table 2.

Mean motivation and preference scores in each VR Group, following each navigation condition.

Standard deviation in parentheses.

Group and Condition	Motivation	Preference
Desktop VR		
Passive	3.83 (1.80)	4.02 (1.93)
Guided	5.02 (1.50)	5.19 (1.53)
Active	5.67 (1.40)	5.19 (1.93)
Headset-based VR		
Passive	4.80 (1.85)	3.72 (1.99)
Guided	5.17 (1.63)	5.13 (1.68)
Active	5.37 (1.52)	5.15 (1.80)

3.3.3 Self-reported Preference

I conducted a 2 (Group: Desktop-VR vs Headset-VR) X 3 (Navigation Condition: Passive, Guided, and Active) mixed ANOVA, with the first factor being between- and the second factor a within-subject manipulation, on self-reported Preference. There was a main effect of Navigation Condition, $F(1.86, 195.09) = 14.82$, $MSE = 4.08$, $p < .001$, $\eta_p^2 = 0.12$, but no effect of Group, $F(1, 105) = 0.62$, $MSE = 2.49$, $p = .434$, $\eta_p^2 = 0.00$. There was no Navigation Condition X Group interaction (see Table 2 for descriptives), $F(1.86, 195.09) = 0.25$, $MSE = 4.08$, $p = .763$, $\eta_p^2 = 0.00$. In both Groups, participants preferred to explore environments under Active and Guided navigation (see Table 2 for means) relative to Passive, $t(106) = 4.70$, $SE = 0.27$, $p < .001$, $BF_{10} = 333.20$, $d = 0.68$, and $t(106) = 4.73$, $SE = 0.27$, $p < .001$, $BF_{10} = 56609.03$, $d = 0.69$, respectively. There were no significant differences in preference ratings between Active and Guided, $t(106) = -0.04$, $SE = 0.27$, $p = 1.00$, $BF_{01} = 9.33$, $d = -0.00$.

3.3.4 Assessment of Path Complexity

I examined whether taking a longer route during encoding (reflecting the topographical properties of the environment) could have influenced route memory. I computed a measure of path complexity for each route taken at encoding. I applied an angle-based measures (see Appendix for a detailed description of the equation) to quantify turns taken while exploring each environment. That is, I recorded each participant's position within each environment, at each 1 second time-point during their 40-second exploration. I then derived displacement vectors between positions at each consecutive time-point. Next, I calculated the angle between each pair of consecutive displacement vectors and normalized these angles to represent a complexity score between 0 and 1, such that a 0-degree turn (straight path) has a complexity of 0, and a 90-degree turn or greater has a complexity of 1. Finally, I tabulated the average of the individual turn complexity scores to determine the overall path complexity in percentage, for each environment within each navigation condition. Figure 9 shows path complexity percentages for all twelve environments explored in a sample participant within Desktop (Panel A) and Headset-VR (Panel B); Active navigation trials are shown in blue, Guided in green, and Passive in black. I tabulated and averaged these scores across all participants, separately by Navigation condition and Group.

I conducted a 2 (Group: Desktop-VR vs Headset-VR) X 3 (Navigation Condition: Passive, Guided, Active) mixed ANOVA, with the first factor being between and the second factor a within-subject manipulation, on Path Complexity scores. There was a main effect of Navigation Condition, $F(1.69, 179.44) = 38.80$, $MSE = 7.96$, $p < .001$, $\eta_p^2 = 0.27$, but no effect of Group, $F(1, 106) = 2.06$, $MSE = 0.01$, $p = .154$, $\eta_p^2 = 0.02$. The Navigation Condition X Group interaction was also non-significant, $F(1.69, 179.44) = 1.95$, $MSE = 7.96$, $p = .152$, $\eta_p^2 = 0.01$. In both Groups, paths explored during the Active condition ($M = 8.8\%$; $SD = 0.03$) were significantly more complex than in the Passive condition ($M = 6.3\%$; $SD = 0.01$), $t(106) = 7.13$, $SE = 0.01$, $p < .001$, $BF_{10} = 18.70$, $d = 0.85$. A similar pattern of results were found when comparing Guided ($M = 9.2\%$; $SD = 0.03$) and Passive conditions, $t(106) = 8.05$, $SE = 0.01$, $p < .001$, $BF_{10} = 43.16$, $d = 0.96$. We did not, however, find a significant difference in path complexity between Active and Guided encoding conditions, $t(106) = -0.92$, $SE = 0.01$, $p = 1.00$, $BF_{01} = 0.21$, $d = -0.11$.

Correlation analyses revealed no significant relationship between Active [$r(106) = -0.03$, $p = .738$], Guided [$r(106) = .16$, $p = .095$], and Passive [$r(106) = -0.10$, $p = .287$] path complexity and route memory performance⁶. These results provide strong evidence that the length of the route taken during encoding, reflecting the topographical properties of the environment and detours, did not influence route memory.

⁶Pearson correlation analyses were collapsed across Group (Desktop-VR and Headset-VR).

Figure 9. *Panel A.* Path complexity and percentage score (shown underneath) from a sample participant from the Desktop-VR group, with Passive trials shown in black, Guided trials in green and Active trials in blue.

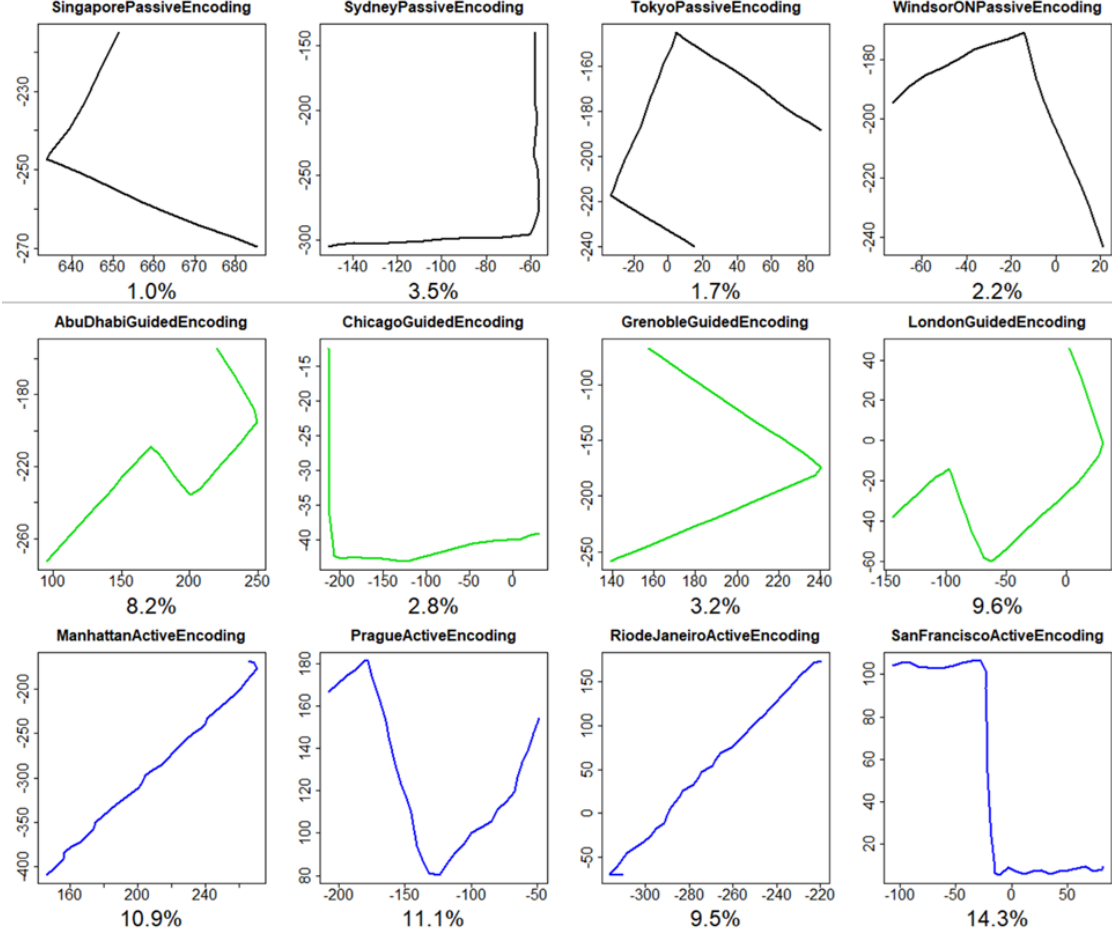
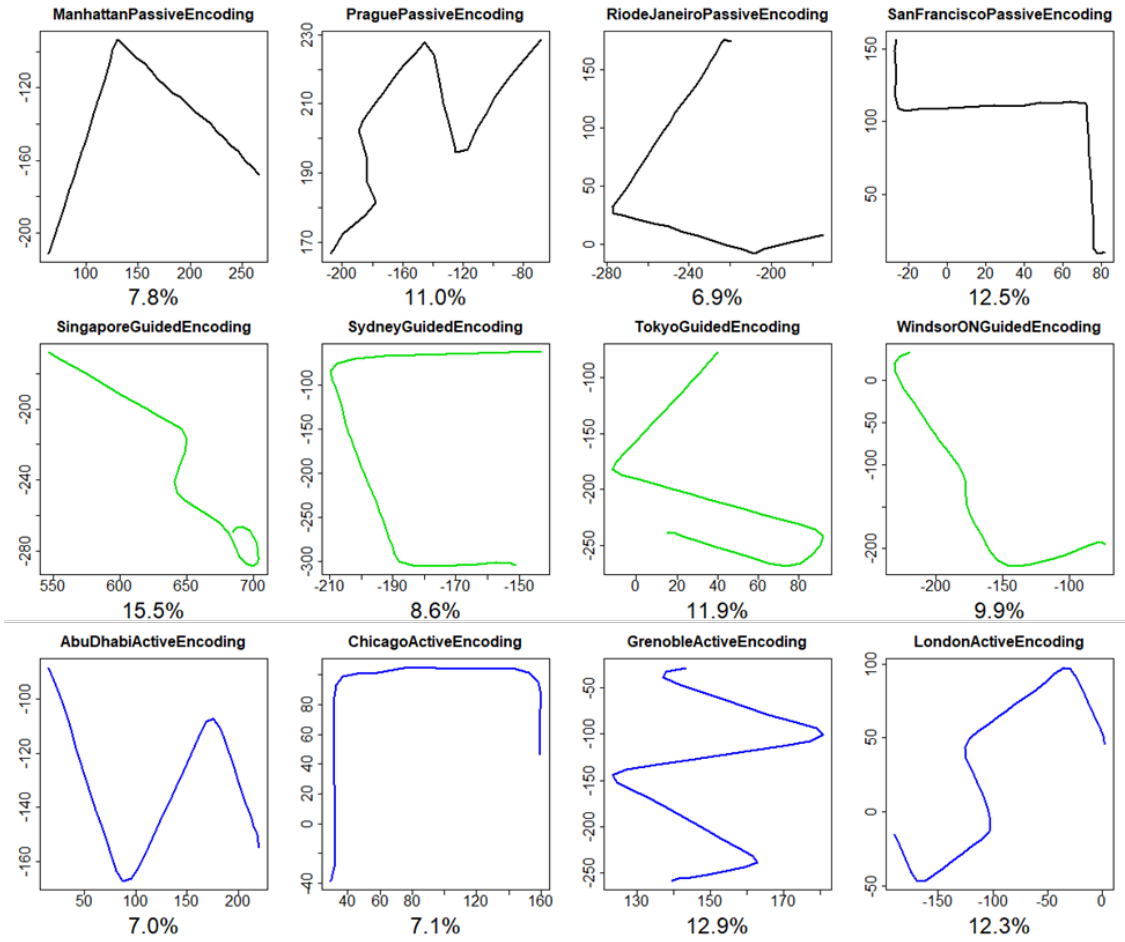


Figure 9. *Panel B.* Path complexity and percentage (shown underneath) from a sample participant from the Headset-VR Group, with Passive trials shown in black, Guided in green and Active in blue.



3.3.5 Correlations with Individual Difference measures

Given my goal of determining whether route memory performance in each of the navigation conditions was related to various individual difference factors (see Table 1 for descriptives for all measures described below), I examined a range of variables. These included intersections, stop count, preference, motivation, spatial navigation proficiency (measured by *SBSODS*), sense of presence in VR (measured by *IPQ*), simulator sickness (measured by *SSQ*), and curiosity (measured by *5DC*). To assess these relationships, I ran a series of Pearson correlations. *IPQ* and *5DC* were further separated into sub-categories: *IPQ* consisted of presence, spatial presence, involvement, and experience realism; *5DC* consisted of joyous exploration, deprivation sensitivity, stress tolerance, social curiosity, and thrill seeking. See Table 3 for correlation coefficients along with significance values.

Table 3.

Pearson correlations in each Group showing association between Route memory following each Navigation condition and various Individual Difference measures.

Variables	Group and Condition					
	Desktop - VR			Headset - VR		
	Active	Guided	Passive	Active	Guided	Passive
1. Intersections Crossed During Encoding	-.27*	.04	-	-.13	.04	-
2. Number of Stops at Intersections During Encoding	.14	.21	-	.16	-.46*	-
3. Total Time at Intersections During Encoding	-.04	.02	-	-.29*	.23	-
4. Stop Count During Encoding	.21	.25	-	.06	-.34*	-
5. Preference	-.12	-.03	-.20	-.37**	-.09	-.16
6. Motivation	-.26	.17	-.04	.00	-.06	-.31*
7. <i>SBSDS</i>	-.04	-.05	.13	-.11	-.12	.15
8. Total Prescence	-	-	-	.08	.01	-.13
9. Prescence	-	-	-	-.03	.03	-.12
10. Spatial Prescence	-	-	-	.08	.09	-.21
11. Involvement	-	-	-	-.11	-.10	.03
12. Experienced Realism	-	-	-	.06	.19	-.06
13. Joyous Exploration	-	-	-	.12	-.31*	-
14. Deprivation Sensitivity	-	-	-	.00	-.21	.29*
15. Stress Tolerance	-	-	-	.02	.19	-.16
16. Social curiosity	-	-	-	-.28*	-.12	.10
17. Thrill seeking	-	-	-	-.23	.06	.18
18. <i>SSQ</i>	-	-	-	.01	.19	.21

Note. * $p < .05$, ** $p < .01$. We did not compute correlations between variables (e.g., intersections crossed, joyous exploration) and route overlap following the passive condition. Since route memory was calculated as deviation in distance, a negative correlation indicates a boost in memory (a reduction in deviation distance).

Intersection Traversed and Dwell Time at Encoding. I found a negative association between the number of intersections traversed and route overlap deviation score, following Active exploration in Desktop-VR. In Headset-based VR, I found a similar relationship between total time spent at intersections (proxy for dwell time) and route overlap deviation following Active exploration

I also detected a negative association between the number of stops made during intersections and along with traveled route with route overlap deviation following Guided exploration in Headset-based VR (see Table 3). This relationship underscores the value of pausing at critical junctures while following GPS instructions. I suggest that stopping at intersections to encode landmarks enhances spatial memory retention, possibly by allowing individuals to encode spatial cues. This can be particularly helpful when navigating new routes, adjusting to changing conditions, or seeking shorter paths under time constraints.

Motivation and Preference Reports. I found a significant negative association between route overlap scores following Passive exploration and motivation in Headset-VR, but not in Desktop VR. I also found that preference for Active exploration was negatively correlated with route overlap deviation for this condition in Headset-VR, but not in Desktop (see Table 3). Collectively, these findings indicate that in highly immersive virtual reality environments, an individual’s intrinsic judgments about the surroundings can augment spatial knowledge.

Curiosity. I found a positive association between deprivation sensitivity and route overlap deviation following Passive exploration in the Headset-based VR group (see Table 3). The items that makeup the “deprivation sensitivity” measure reflect the negative feelings (e.g., anxiety and frustration) that one experiences when the right information is concealed from them. When deprivation sensitivity is present, people experience discomfort and annoyance until they resolve information gaps (e.g., Litman, 2005). It is interesting to observe that participants who scored high on this measure also had poorer memory for routes travelled at encoding during Passive exploration (i.e., higher route memory deviation). In contrast, we found joyous exploration and social curiosity to be negatively associated with route overlap deviation following Guided and Active explorations, respectively. These results do indeed highlight the dual nature of curiosity, showing that while a positive state of curiosity (i.e., joyous exploration and social curiosity) can boost cognitive performance, a negative state (i.e., deprivation sensitivity) of curiosity may impair it.

3.3.6 Predictors of Route Memory Performance

A forward stepwise regression analysis was conducted (separately for Desktop- and Headset-based VR groups) to identify the strongest predictors of route memory performance following Active, Passive, and Guided exploration. I included the following measures in our model, as predictors: intersections crossed at encoding, distance travelled, total time spent within an intersection, path complexity, motivation, preference, scores on the Santa Barbara Sense of Direction Scale (*SBSODS*), the Igroup Presence Questionnaire (*IPQ*), the Simulator Sickness Questionnaire (*SSQ*), and the Five-Dimensional Curiosity Scale (*5DC*).

Desktop-VR Group. For the Active condition, the final model was statistically significant, $F(2, 51) = 4.43$, $p = .017$, and explained approximately 12% of the variance in route memory performance (adjusted $R^2 = .115$). The first variable entered into the model was intersections crossed at encoding, which significantly predicted route memory following Active exploration, $\beta = -7.99$, $t = -2.43$, $p = .019$. This means that a one-unit increase in intersections crossed at encoding leads to a 7.99 decrease in deviation distance (better memory). The second variable entered was motivation, which also significantly predicted route memory performance, $\beta = -3.37$, $t = -2.12$, $p = .039$. Here, we can also infer that a one-unit increase in motivation ratings leads to a 3.37 decrease in deviation distance (better memory).

For the Guided condition, the final model was statistically significant, $F(1, 52) = 4.72$, $p = .034$, and explained approximately 7% of the variance in route memory performance (adjusted $R^2 = .066$). I only found self-report scores on the Santa Barbara Sense of Direction Scale (*SBSODS*) to significantly predict route memory, $\beta = -8.64$, $t = -2.17$, $p = .034$. This means that a one-unit increase in *SBSODS* self-ratings leads to an 8.64 decrease in deviation distance (better memory).

For the Passive condition, a similar stepwise regression analysis was performed to identify predictors of the outcome variable. However, no variables met the criteria for inclusion in the final model. As a result, the model did not include any predictors, and the variance explained was effectively zero ($R^2 = .00$).

Headset-VR Group. For the Active condition, the final model was statistically significant, $F(2, 48) = 7.52$, $p = .001$, and explained approximately 21% of the variance in route memory performance (adjusted $R^2 = .207$). The first variable entered into the model was preference, which significantly predicted route memory following Active exploration, $\beta = -1.98$, $t = -3.18$, $p = .003$. This means that a one-unit increase in preference ratings leads to a 1.98 decrease in deviation distance (better memory). The second variable entered was the social curiosity subscale from the five-dimensional curiosity scale, which

also significantly predicted route memory performance, $\beta = -2.77$, $t = -2.53$, $p = .015$). This indicates that a one-unit increase in the curiosity subscale leads to a 2.77 decrease in deviation distance (better memory). For both Guided and Passive conditions, a similar stepwise regression analysis was performed to identify predictors of the outcome variable. However, no variables met the criteria for inclusion in the final model. As a result, the model did not include any predictors, and the variance explained was effectively zero ($R^2 = .00$).

3.3.7 Exploratory Mediation Analysis

To determine whether the effect of navigation type on route memory in both Desktop and Headset-VR groups was mediated by self-reported motivation to explore under each navigation type, we conducted two mediation models (see Figures 10 and 11) using SPSS Process macro (Hayes, 2018). As confirmed by indirect paths based on 5000 bootstrap resamples, motivation did not emerge as a significant mediator in either the Desktop or Headset-VR groups.

Figure 10. Mediation model for Desktop-VR group examining whether the effect of navigation type (Active as reference; Passive, Guided) on Route Memory was mediated by self-reported motivation to explore under each navigation type. Standardized Linear Regression Coefficients (β) along with confidence intervals (based on 5000 bootstrap resamples) and p -values are shown.

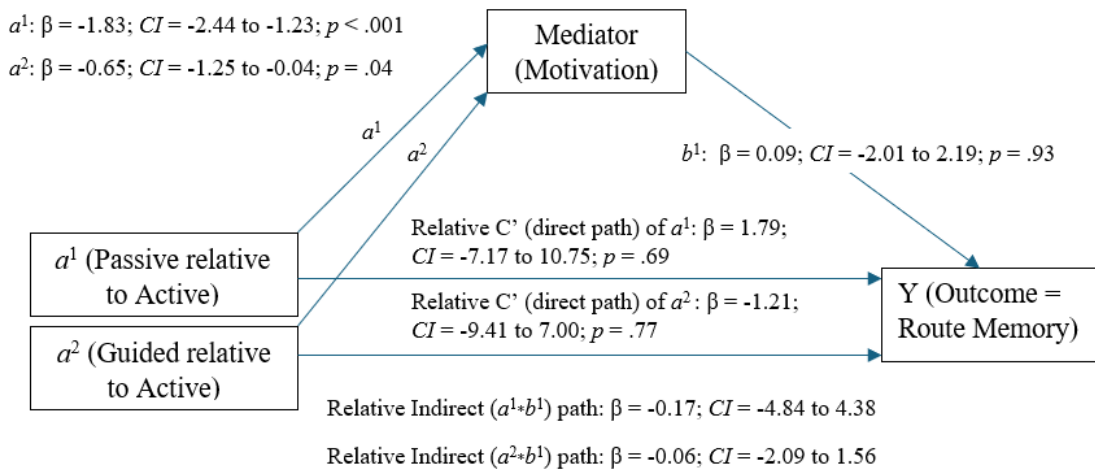
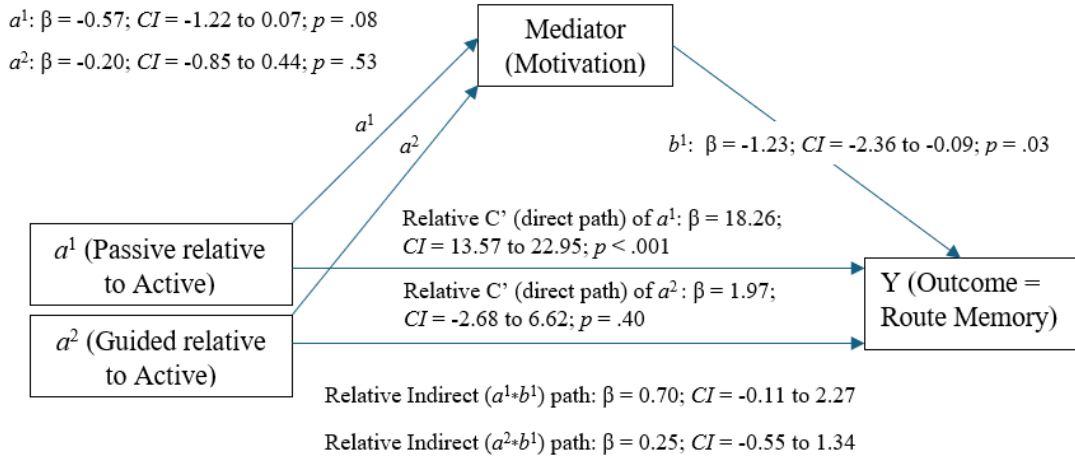


Figure 11. Mediation model for Headset-VR group examining whether the effect of navigation type (Active as reference; Passive, Guided) on Route Memory was mediated by self-reported motivation to explore under each navigation type. Standardized Linear Regression Coefficients (β) along with confidence intervals (based on 5000 bootstrap resamples) and p -values are shown.



3.4 Discussion

In the current research, my objective was to examine the relative contribution of decision-making and motor engagement at encoding, on route memory, using VR. I manipulated the need for decision-making during encoding of a new route, as well as the motoric demands for movement, to determine their relative influences on memory. Movement was initiated using a QWERTY keyboard and finger movement to navigate keys during Desktop viewing of environments, with limited motoric engagement, or within a VR headset using a compatible steering wheel that allowed for greater motoric involvement. Using Headset-based VR but not Desktop VR, I found that route memory was significantly better following Active and Guided relative to Passive trials. Importantly, I showed that memory did not differ following Active relative to Guided trial types, suggesting that decision-making does not underlie the memory benefit. Taken together, these findings suggest that motoric engagement, more so than decision-making, is necessary to enhance memory for routes.

These results highlight the importance of active engagement and self-motion cues in spatial navigation, supporting the idea that more immersive and physically engaging navigation experiences lead to better retention.

That I observed a significant effect of encoding strategy in the Headset-based VR but not in the Desktop version underscores the importance of self-motion cues in enhancing route memory. In the Desktop version, participants navigated along routes via keyboard button presses alone, which represents a comparatively reduced engagement of motor activity. In addition, I speculate that movement via keyboard button press limited the level of realism afforded by the virtual environment, and in turn, made it challenging for participants to track their position within the virtual environment. Typically, past studies investigating route memory have shown that active navigation at encoding leads to better memory than passive (Chrastil & Warren, 2012). However, some studies report no differences between these conditions; importantly, this has occurred in studies that implemented Desktop VR (Gaunet et al., 2001; Wilson, 1999; Wilson et al., 1997). Given that I observed similar route memory performance across the three encoding trial types in our Desktop but not Headset-based VR group, I propose that the limited motor and sensory feedback in the former likely accounts for this finding in other work (Smith, 2017; Roettl & Terlutter, 2018). For example, Roettl and Terlutter (2018) examined how variations in VR display (desktop versus immersive VR systems) and user interface (e.g., steering wheels, handheld controllers) could influence users' ability to navigate and remember spatial information. One of their key findings was that immersive VR systems provide precise spatial cues about the virtual environment compared to Desktop viewing. Further, Smith (2017) explored the role of self-motion cues in spatial navigation, particularly focusing on how the vestibular and proprioceptive systems contribute to route memory and navigation performance. Participants who received more robust self-motion cues performed better in navigation tasks, demonstrating improved route memory and spatial orientation relative to those with limited or no self-motion cues. The current study supports Smith's (2017) finding, as I also detected the memory benefits of active and guided navigation, but only in the Headset-based VR group. Overall, these findings highlight that effective spatial navigation, particularly when remembering route information, is strengthened by the integration of multiple self-motion cues.

3.4.1 Possible Neural Mechanisms Underlying Navigation

The effect of navigation strategy in the Headset-based VR study, but not in the Desktop VR, signifies that an immersive experience matters to performance on egocentric spatial tasks such as route memory. Egocentric navigation is said to depend on inertial cues

that engage the dorsal striatum, facilitating encoding of routes and procedural memories (Vorhees & Williams, 2014). Inertial cues include proprioceptive feedback from sensory receptors in muscles and joints, vestibular information from the inner ear that detects head position and motion, and accelerative cues signalling changes in velocity, all of which contribute to the perception of self-motion (Jerald & Marks, 2016). When interpreting the findings of the current study in the context of prior research we infer that the route learning task used here also heavily depends on the striatal and other motor regions of the brain.

Route memory involves sequences of decisions such as “go straight, turn right, then turn left”, which require specific actions at key intersections (Ruddle et al., 2011). Since participants were required to retrace the exact route during retrieval, their memory likely depended on striatal regions, as it is involved in recalling sequences of actions, mediated by this region (Burgess, 2008). Although the Guided condition removed the need for decision-making, it still provided participants with sufficient inertial cues, including proprioceptive, vestibular, and visual flow information. It is this information that we believe participants utilized later to retrieve the exact route taken during encoding. Another notable observation in our data is that route memory performance in the Guided condition differed significantly from that in the Passive condition (in the Headset-based VR group). This finding once again suggests that the motor information available during Guided exploration was sufficient to enhance memory compared to Passive exploration. Moreover, the lack of a significant benefit of navigation strategy on route memory performance in Desktop but not Headset-based VR implementation provides additional evidence that environments offering enhanced self-motion cues can better support route memory.

3.4.2 The Role of Individual Differences in Spatial Navigation

My findings also underscore the role of individual differences in shaping spatial navigation performance across immersive and non-immersive virtual environments. Specifically, in Desktop-VR, participants who crossed more intersections during Active exploration exhibited better route memory performance. Similarly, in Headset-VR, the total time spent at intersections during Active exploration was negatively associated with route overlap deviation (indicating better memory performance). These results align with prior animal research indicating that intersections serve as salient spatial boundaries, helping to contextualize cognitive maps (Moser et al., 2008). Notably, in Headset VR, pausing at intersections and along the route during Guided navigation was linked to improved memory. This reveals that brief pauses may facilitate the encoding of spatial cues and ultimately

enhance spatial memory, even when navigation is guided. These findings are further supported by the regression results, which revealed that in Desktop-VR, route memory in the Active condition was predicted by the number of intersections traversed, while Guided memory was predicted by navigation proficiency measured by *SBSODS* scores.

Further, intrinsic qualities such as motivation and preference also played a significant role in shaping memory outcomes. In Headset-VR, a stronger preference for Active exploration was linked to, and predicted, higher route memory performance in this condition. This is consistent with the higher preference ratings observed for Active relative to Passive encoding strategies. These regression results, however, were not detected in the Desktop VR group, even if participants preferred Active and Guided conditions relative to Passive. Collectively, these results emphasize that aligning navigation strategies with user preferences could positively impact memory performance, especially in highly immersive settings. On the other hand, motivation predicted better route accuracy following Active exploration in the Desktop-VR group, which is reflected in the higher motivation ratings observed for this condition relative to Guided and Passive. I suspect that in low-immersion settings, such as Desktop-VR and in Passive conditions that reduce user engagement, maintaining attention may be difficult, limiting route memory.

Further, positive dimensions of curiosity such as joyous exploration and social curiosity were associated with improved memory following Active and Guided exploration, respectively. While negative dimensions such as deprivation sensitivity was linked to poorer memory following Passive conditions. Regression models further supported these observations, with social curiosity predicting route memory performance following Active exploration in the Headset-VR group. This suggests a dual effect: curiosity can either enhance or hinder spatial encoding depending on its emotional valence and whether the environment allows for information-seeking behavior. Indeed, the Prediction, Appraisal, Curiosity, and Exploration (PACE) framework proposed by Gruber and Ranganath (2019), proposes that an anxious state could lead to behavioral inhibition, potentially diminishing memory performance. In line with this, Brunyé and colleagues (2009) showed that spatial representations formed during high arousal states tend to have more global configural details about the broader inter-landmark structure of an environment. In contrast, a low arousal state diminished participants' ability to accurately compare distances between landmarks that are relatively far as opposed to close to one another. These results show that various emotional and arousal experiences can differentially influence how we encode and retrieve spatial information, highlighting the nuanced role of emotions in cognitive processes related to navigation and memory.

3.4.3 Conclusion

The findings of this Chapter indicate that self-generated motoric engagement, needed in both active and guided navigation conditions, enhances formation of route memory relative to passive observation. That is, I have demonstrated that self-motion cues, such as head rotations, full-body 360-degree turns, and forward movement via handheld controller, during initial exploration of a virtual environment support route knowledge. Decision-making, in comparison, seems to play a lesser role as memory did not differ across navigation conditions that required it (Active) versus not (Guided). Moreover, the selective finding of a memory benefit in the Headset-based VR, but not the Desktop VR group, provides additional evidence that environments offering the opportunity for motor engagement better support route memory. These findings also have implications for the development of navigation systems for humans. Relying on external GPS devices (analogous to the guided condition in the current study) for navigation is unlikely to impair memory for the routes, as others have suggested (Bakdash et al., 2008; Gardony et al., 2013), provided that the motor system is engaged during the initial encoding phase.

Chapter 4

The use of decision-making to mitigate age-related differences in spatial memory

4.1 Introduction

Age-related atrophy in motor regions such as the central sulcus, premotor cortex, intraparietal sulcus, insula, frontal operculum, and cerebellar vermis (Ward and Frackowiak, 2003) may reduce motor function in older adults. This may lead them to depend more on self-initiated decision making to support route memory. For example, older adults who experience difficulties with fine motor skills, coordination, and dexterity struggle with tasks that require anticipatory planning and full-body coordination, such as navigation (Ward and Frackowiak, 2003). In animal research, particularly with rodents, it has been demonstrated that motion cues are vital for forming and maintaining spatial representations (Vorhess & Williams, 2014). For example, animal studies have shown that impairments to the vestibular labyrinths in the inner ear, a key structure involved in the processing of vestibular information, leads to deficits in performance on the Morris Water Maze task (Frissen et al., 2011). Similar results have been observed in humans, with findings demonstrating that age-related vestibular loss negatively impacts older adults' ability to perform spatial tasks such as angle rotation estimates for path integration (Coto et al., 2021). Moreover, studies in humans have shown that vestibular based self-motion cues can enhance egocentric route learning (Jabbari et al., 2021). The basal ganglia structures which also undergo age related changes have been reported to play a crucial role in the execution

of rehearsed or trained motor sequences (Marchand et al., 2011).

Therefore, there is reason to believe that older individuals may gain differentially from active navigation strategies that allow for self-initiated decision-making about the travel path, and would suffer when decision-making is removed, as in cases of guided navigation. For example, neural evidence indicates that self-initiated decision-making during navigation strengthens connectivity between frontal and hippocampal regions (Euston & McNaughton, 2012; Konishi & Bohbot, 2013); these are the brain areas subject to the most deterioration as a result of aging. As well, other research suggests that having a sense of agency, which is limited when using GPS devices, can serve to benefit memory (Hon & Yeo, 2021). Similarly, research has shown that a lack of perceived control can reduce memory in older adults (Lachman & Agrigoroaei, 2012), therefore the use of GPS may have negative consequences.

4.1.1 Current Study

Given these past findings, I expected that navigation conditions that require motor control would benefit memory in younger (Sivashankar et al., 2024), as well as older adults. Older adults, however, may selectively benefit from navigation conditions in which they are forced to engage in decision-making, and retain agency (Hon & Yeo, 2021). In other words, navigation with reliance on GPS-type guidance may selectively hamper memory in older but not younger adults. Based on past research I also suggest that landmark memory, which relies on heightened self-awareness of the environment, would be facilitated by active exploration (Chrastil & Warren, 2012).

My research had two primary objectives. First, I sought to determine whether providing visual navigational guidance during initial exploration of a space hindered memory for routes travelled, and landmarks contained therein. Second, I compared route and landmark memory across age groups, young and old. To examine these research questions, participants explored 12 environments within virtual-reality (VR) in one of three ways: (1) viewing a video of a pre-recorded path of travel along roads within virtual cities, with no volitional motor or decision-making control (hereafter referred to as ‘passive’ exploration), (2) freely exploring an environment while making decisions about where to turn and move (hereafter referred to as ‘active’ exploration), or (3) receiving visual guidance to a final destination (hereafter referred to as ‘guided’), thereby limiting cognitive decision-making while maintaining the ability to move oneself along the city streets. The use of VR allowed me to simulate real-world environment layouts of cities around the world (e.g., Tokyo, New York), and to examine both the physical and cognitive contributions to route

and landmark memory. To assess memory for routes travelled at encoding, participants were placed at the exact same starting position within each VR environment and were instructed to reproduce the same path they had taken during initial exploration. I also assessed item recognition memory for landmarks seen during exploration.

4.1.2 Individual differences

Past research on individual differences in navigation has consistently highlighted that people vary in their ability to navigate through physical and virtual environments (Chen et al., 2000; Moffat, 2009; Newcombe & Hegarty, 2023, Weisberg & Newcombe, 2016). These differences are often influenced by factors such as spatial ability, experience, motivation, and emotional states. For example, studies have shown that individuals with higher spatial abilities or those who are more familiar with navigation tasks perform better in route memory tasks (Hegarty et al., 2006). Further, emotional states, including curiosity and motivation, have been linked to navigation success, suggesting that the psychological factors driving how individuals engage with their environment may play a significant role in how they encode and recall spatial information (Sauz  on et al., 2016; Sivashankar et al., 2024). Furthermore, the concept of presence in virtual environments has been found to impact cognitive performance, including memory retention, with more immersive experiences enhancing memory (Schubert et al., 2001). These findings underline the importance of considering individual differences when studying navigation and memory performance.

Given these suggestions of individual differences, I asked participants in our study to complete several scales upon completion of the VR component of the experiment. We assessed their everyday navigation abilities using the *Santa Barbara Sense of Direction Scale* (Hegarty et al., 2006; *SBSODS*), and self-reported motivation and preferences for the three navigation conditions (passive, guided, and active). In addition, participants completed the Five-Dimensional Curiosity Scale (*5DC*), which assesses participants’ inherent qualities of curiosity related to joyous exploration, deprivation sensitivity, stress tolerance, social curiosity, and thrill seeking (Litman, 2005). In my past research, I demonstrated a significant link between curiosity and route memory performance in children (Sivashankar et al., 2024). In this study, we aimed to explore whether individual differences might affect route memory. Such an examination has broader implications for understanding the influence of curiosity on memory. Lastly, I assessed simulator sickness (Kennedy et al., 1993; *Simulator Sickness Questionnaire*) and participants’ sense of presence in VR (Schubert et al., 2001; *Igroup Presence Questionnaire*) to gauge the “realness” of the virtual environments, as these factors might indirectly influence memory performance for the routes traveled in VR.

4.2 Methods

Participants. After conducting a power analysis using G*Power software (version 3.1), a sample size of 43 participants or greater was deemed necessary to achieve 95% power to detect a medium-sized (Cohen’s $d = 0.5$) main effect in a within-subjects design (i.e., a one-way repeated measures), with an alpha level of 0.05 (Field, 2005). In addition to this, a power analysis was also performed to assess the necessary sample size for detecting between-subjects age differences and the interaction effect between age group (younger vs. older adults) and navigation condition (active, guided, passive). This analysis indicated that a sample size of 44 participants per group (88 total) would be required to achieve 95% power for detecting a medium-sized interaction effect, based on an alpha level of 0.05.

Fifty-four young adult undergraduate students (35 males, 19 females; $Age = 22.0$, $SD = 3.20$) from the University of Waterloo were recruited on a volunteer basis to participate in the study. Data collection in undergraduates took place between October 2023 to January of 2024.

I had also aimed to collect a similar number of participants in the older adults group. I recruited 44 participants, but only 20 (13 males, 7 females; $Age = 78$, $SD = 2.20$) were able to complete the study as a result of motion sickness. Data collection in older adults took place between March to October of 2024. All older adults achieved a MoCA (Nasreddine et al., 2005) score equal to or greater than 26 ($M = 28.12$, $SD = 1.54$). To overcome the issue of unequal sample size, I conducted analyses using the full sample of younger adults; as well, I created a sample based on the full young adult dataset, that matched the sample size of older adults. To this end, I randomly selected a sample of twenty participants from the younger sample to conduct the analyses examining age effects on route and landmark memory performance. Although this study fell short of the target sample for detecting an interaction effect between age groups, previous studies in aging and VR have recruited similar sized samples of older adults (e.g., see Review by Fricke et al., 2022), likely due to the difficulty in recruiting participants who could complete VR studies. The Research Ethics Committee at University of Waterloo approved all study procedures. Written informed consent was obtained from all participants prior to experimentation.

Materials. VR-Application: A computer-run VR application was designed on the 3D Unity © engine (ver. 2019.4.4f1; see specifications on <https://www.vive.com/ca/>), using the software Mapbox (<https://www.mapbox.com/>). Mapbox generates game objects for roads and structures using open-source geolocation data and 3D scans of buildings, requiring a GPS position and a zoom scale to specify the perimeter of the location that is being simulated. Unity © engine is a game development platform used to create virtual environments for players to explore. In my experiment, I paired a VR immersion plugin with

3D Unity © engine that generated game objects using geolocation data from real cities, creating an application that allowed participants to use VR headsets to virtually explore custom-created 3D environments based on real-world environment layout of selected cities.

The VR application included 12 Virtual Environments (VEs) created by entering the longitudinal and latitudinal coordinates of various cities around the world (e.g., Abu Dhabi, Chicago, Grenoble, London, Manhattan, Prague, Rio de Janeiro, San Francisco, Singapore, Sydney, Tokyo, Windsor) into the Mapbox Environments SDK for Unity © engine. Our VR application allowed participants to explore VEs with a lightweight HTC VIVE headset (HTC Corporation; Valve Corporation) and handheld controllers, with continuous button press and heading rotation, for an easy-to-use control interface. Environments in our VR program were chosen to contain sufficient path complexity, and to be equivalent in environment sizes. Path complexity was operationalized to be the number of intersections (i.e., total possible turns) contained in each environment. Google Maps Street™ View was then used to decide specific streets within an environment to include in our VR program. Environments were all topographically (i.e., structural organization of the environment) similar, with an average area of 100,000 square meters (measured using Google Earth™ polygon tracing) with a minimum of 4 and a maximum of 20 intersections (point at which two or more roads converged). Since I created the environments to simulate how the cities appear in the real world, some environments contained a greater number of intersections than others. Following environment selection, I integrated landmarks into each environment according to observations made from Google Maps™ Street View. These landmarks were 3D models of various objects that are commonly observed throughout a city, such as benches, trees, water fountains, bus stops, and traffic lights, downloaded from the free-to-use online source, Sketchfab (sketchfab.com). Finally, the velocity at which participants moved in VR was set at 8ms/sec (analogous to a vehicle going approximately 30 km/hr) within each exploration of an environment.

Measures. Calculation of route overlap as a measure of route memory: The primary dependent variable of interest was the accuracy in reproducing the exact same route at retrieval that had been travelled during encoding of environments. To obtain this measure of spatial memory performance, the deviation in distance between the routes travelled by each participant at encoding and retrieval, for each of the 12 environments was calculated to produce a deviation distance measure¹. Specifically, for every environment, we collected 40 pairs of X, Y coordinates every second, during both initial exploration (encoding) and retrieval, reflecting a participant's position in an environment. Using the *Pythagorean theorem*, the Euclidean distance was calculated [$d = \sqrt{((x^2-x^1)^2 + (y^2-y^1)^2)}$] between each

¹Mean deviation distance was computed for each environment explored (12 environments in total) separately for each condition, i.e. 4 passive, 4 guided, 4 active environments, for each participant.

of the 40 X, Y coordinates from encoding and retrieval (Liberti et al., 2014). We then calculated the average distance (d) value to obtain the mean deviation distance between Encoding and Retrieval for each environment, explored by a participant. A higher value signified that there was greater deviation between the paths making up encoding and retrieval, hence, poorer memory for the route travelled at encoding. Finally, we computed the mean route overlap across the four environments in each of the three conditions to obtain a single route overlap value that was the most representative of route memory following passive, guided, and active exploration.

Calculation of landmark memory performance: To measure memory for landmarks observed during exploration of environments, participants completed an item recognition test at the very end of the experiment. This landmark test was incidental. That is, participants did not know during exploration that they would later be asked to recognize target objects encountered in the environments. A total of thirty-six targets (12 per navigation condition; Active, Passive, and Guided), and 36 semantically related lures were shown in a sequential manner. Presentation of each target was displayed on the screen for 3 seconds, following a fixation cross centrally displayed for 500 milliseconds. Participants had up to 3 seconds to respond by pressing the "M" key for old items and the "N" key for new items. Hit rates were calculated by dividing the number of correctly identified targets by the total number of items shown for each navigation condition. For instance, if a participant recognized 7 out of 12 items from the Active condition, their hit rate would be 0.58. This method was used to compute hit rates for the Passive and Guided conditions as well, for each participant (see Figure 13 for average hit rates by age group).

Individual difference measures administered post VR-immersion: A second goal of our work was to document the relationship between individual differences in navigation abilities, preferences or motivations for various encoding types, and how trait-level curiosity influences memory performance.

Santa Barbara Sense of Direction Scale: I asked participants to complete a questionnaire to assess their everyday navigation skills using the *Santa Barbara Sense of Direction Scale* (*SBSODS*; Hegarty et al., 2006). The goal of this measure was to help us determine whether inherent visuospatial skills influenced route memory performance, beyond our experimental manipulation. Each participant rated their endorsement of 15 statements about spatial orientation in everyday life, such as "I am good at giving directions", indicating whether they strongly agreed or disagreed, using a 7-point Likert-scale. After reverse scoring the items, the responses were summed and divided by 15 to derive an average score between 1–7.

Preference and Motivation: I measured variations in self-reported motivation and

preference for each navigation strategy (passive, guided, and active) and examined whether this influenced route memory. Previous research has highlighted the critical role of motivation in enhancing spatial memory across different age groups, including children, younger and older adults (Gruber et al., 2014; Sakaki et al., 2018; Sivashankar et al., 2024). We specifically aimed to determine whether participants felt more motivated to explore in the active and guided conditions compared to the passive condition, as this could explain any subsequent memory benefits. To this end, participants rated their motivation and preference to explore each condition (passive, active, and guided), on a 7-point Likert-scale, with increasing numbers reflecting greater motivation or preference (e.g., “Please rate your motivation to explore environments in VR during active exploration”; “Please rate your preference to explore environments in VR during active exploration”).

Five-Dimensional Curiosity Scale (5DC): This questionnaire assesses participants’ inherent qualities of curiosity related to joyous exploration, deprivation sensitivity, stress tolerance, social curiosity, and thrill seeking (Litman, 2005). In our past research, we have demonstrated a significant link between curiosity and route memory performance (Sivashankar et al., 2024). In this study, I also aimed to explore whether individual differences in the emotional states elicited by curiosity, such as feelings of joy versus fear, might affect route memory. Such an examination has broader implications for understanding the influence of curiosity on memory.

Simulator Sickness and Presence: I then measured simulator sickness using the *Simulator Sickness Questionnaire (SSQ)* (Kennedy et al., 1993) to evaluate oculomotor discomfort, disorientation, nausea, and fatigue experienced as a result of VR exposure. We scored this questionnaire by assigning each question a value based on the response. Each “None” response received a score of 0, each “Slight” response received a score of 1, each “Moderate” response received a score of 2, and each “Severe” response received a score of 3. Based on a large sample of *SSQ* data gathered from military pilots, it is suggested that total scores can be associated with negligible (< 5), minimal (5 – 10), significant (10 – 15), and concerning (15 – 20) symptoms (Kennedy et al., 1993).

Finally, I administered the ***Igroup Presence Questionnaire (IPQ)*** to determine the extent to which participants felt present while exploring the VR environments (Schubert et al., 2001). Participants were instructed to rate each statement (e.g., “In the computer-generated world, I had a sense of being there”, “I felt present in the virtual space”) from a scale of 1 (not at all) to 7 (very much). To gain a more comprehensive understanding of various related factors associated with presence, items measuring sense of presence, spatial presence, involvement, and experienced realism were also assessed and considered. Therefore, for the *IPQ*, I obtained four scores corresponding to the subscales, along with a total score, which was calculated by averaging all the individual scores and dividing by

the total number of items (14).

Montréal Cognitive Assessment (MoCA): Following these test measures, only the older adults completed the *Montréal Cognitive Assessment* (*MoCA*; Nasreddine et al., 2005); a test designed to screen for general cognitive impairment. Participants were excluded from our main reported analyses if their *MoCA* score was less than 26. The most commonly used and accepted *MoCA* cut-off for healthy aging is 26/30. Lower scores indicate mild cognitive impairment or dementia (Nasreddine et al., 2005).

Procedure. Throughout the entire VR experiment, participants, both younger and older adults, were seated in a comfortable swivel chair that could turn a full 360°, placed in the center of a testing room. Following verbal instructions on how to use the VR headset, participants completed a practice phase with the VR equipment, designed to help them learn how to use the VR controllers to move within the virtual space. A single handheld VR controller was sufficient to navigate in the environment. To move forward, participants were instructed to press the Trackpad Button of the controller using their thumb, repeatedly swiping it forward to move. To change their direction, participants had to rotate their head in the desired direction, as well as physically rotate in the spinning chair with their legs, while pressing the Trigger button on the VR controller, pointed in the direction of travel. I advised participants to take as much time as needed in the training phase in order to become comfortable with the environment. Immediately following the training phase, the experimental session began.

There were two main phases for each of the 12 environments: A study/encoding phase (40 secs), and then a retrieval phase (40 secs) which followed immediately, in which participants were asked to reproduce the exact route taken at encoding. During the study in each of the 12 environments within VR, they were given one of three navigation strategies: Passive, Guided, and Active. There were manipulated within-subject, with navigation condition and order counterbalanced across participants.

The passive condition was created by recording 360-degree videos of a pre-defined path for each environment. Therefore, the path observed by participants in the passive condition differed from the paths travelled in the guided and active conditions. That is, we did not yoke the passive condition trials to a route travelled in the active or guided conditions. Participants observed the environment within VR in a manner similar to being a passenger inside a vehicle, being driven by another person. During passive viewing (see Figure 2), participants were provided with the following instructions: “You will passively explore this environment. During passive exploration, you will experience a tour of the environment leading you to a gold star. You will be able to move your headset, but will have no control over the movement of your hand-held controllers”. To reiterate, participants did not exert

motor control for movement, nor decide the path of travel.

The guided condition was created using Mapbox Directions API to automatically generate the optimal path between two waypoints according to path data. Specifically, one end of the waypoint was attached to a fixed location (the gold star; destination), while the other waypoint was attached to the participant so that the path could be updated in real time. This path was colored in Yellow (see Figure 2) and overlaid onto the travelled path so that it was highly visible to participants. During guided exploration, participants received the following instructions “You will be guided during exploration of this environment. During guided exploration, you will follow a yellow-line directing you to a gold star”. Simply put, during the guided exploration, participants exerted motor control using the VR controllers (along with head and body rotation) to move forward and follow the yellow line directing them to their end-point, but did not decide the path of travel.

During active exploration (see Figure 2), participants were free to choose the route they travelled to find a gold star. That is, participants exerted motor control using the VR controllers, and also decided the path of travel, thus, engaging both motor and decision-making processes. Therefore, the paths travelled in the guided and active conditions differed as the former path was experimentally controlled, while the latter was chosen by the participant. Prior to beginning each new exploration, an instruction appeared on the screen indicating the condition. Immediately after encoding (40 secs) a given environment, participants were placed back at the same starting position, and asked to reproduce (move themselves) along the route they had taken during initial exploration (encoding).

Each participant explored all 12 environments. Encoding conditions were blocked by type (4 environments of Passive, 4 environments of Guided, and 4 environments of Active). The order of the three condition blocks (Passive, Guided, and Active) was counterbalanced across participants. The total time spent in VR was approximately thirty minutes (including a break to reduce VR fatigue, before starting a new condition). After completion of the experiment in VR, participants were asked to complete the landmark memory test. To reiterate, the landmark assessment was incidental; participants were unaware during exploration that they would later be asked to remember the targets they had seen during encoding of environments. After the completion of the landmark assessment, questionnaires were administered.

4.3 Results

4.3.1 Route Overlap (memory) Performance

I conducted a 2 (Group: Young vs Old) X 3 (Navigation Condition: Passive, Guided, and Active) mixed Analysis of Variance (ANOVA), with the first factor being between- and the second factor a within-subject manipulation, on Route Overlap scores (see Figure 12). There was a main effect of Navigation Condition, $F(2, 76) = 12.00$, $MSE = 203.16$, $p < .001$, $\eta_p^2 = .24$. Both Active ($M = 26.50$, $SD = 11.22$) and Guided navigation ($M = 31.69$, $SD = 14.14$) improved route memory compared to Passive navigation ($M = 41.85$, $SD = 17.56$). There was no difference between Active and Guided performance. There was also a main effect of Group $F(1, 36) = 11.72$, $MSE = 321.77$, $p = .001$, $\eta_p^2 = 0.24$. Specifically, younger participants showed significantly less route deviation compared to older adults, indicating better memory. As predicted, I also observed a significant Group X Navigation Condition interaction, $F(2, 76) = 3.22$, $MSE = 203.16$, $p = .044$, $\eta_p^2 = 0.08$. To understand the interaction, I conducted separate one-way ANOVAs for each Group.

Younger Group. I conducted a one-way repeated measures ANOVA to examine the effect of Navigation Condition on route overlap score as the dependent variable. There was a significant effect of Navigation $F(2, 38) = 5.20$, $MSE = 188.21$, $p = .010$, $\eta_p^2 = 0.22$ (see Figure 12 for means)². Paired sample t -tests showed that passive exploration resulted in the highest mean deviation score relative to Active and Guided navigation conditions, $t(19) = 2.28$, $SE = 3.72$, $p = .035$, $BF_{10} = 1.86$, $d = 0.51$, and $t(19) = 2.99$, $SE = 2.18$, $p = .007$, $BF_{10} = 6.60$, $d = 0.67$, respectively³. We chose to report Bayes Factors alongside traditional p-values for two main reasons. First, we wanted to provide the reader with both results so that they could better interpret the evidence being reported. Second, reporting Bayes Factors allows for the evaluation of evidence that is consistent with the null hypothesis, lending to more meaningful interpretation. There was no significant difference between Active and Guided exploration on route overlap score, $t(19) = 0.72$,

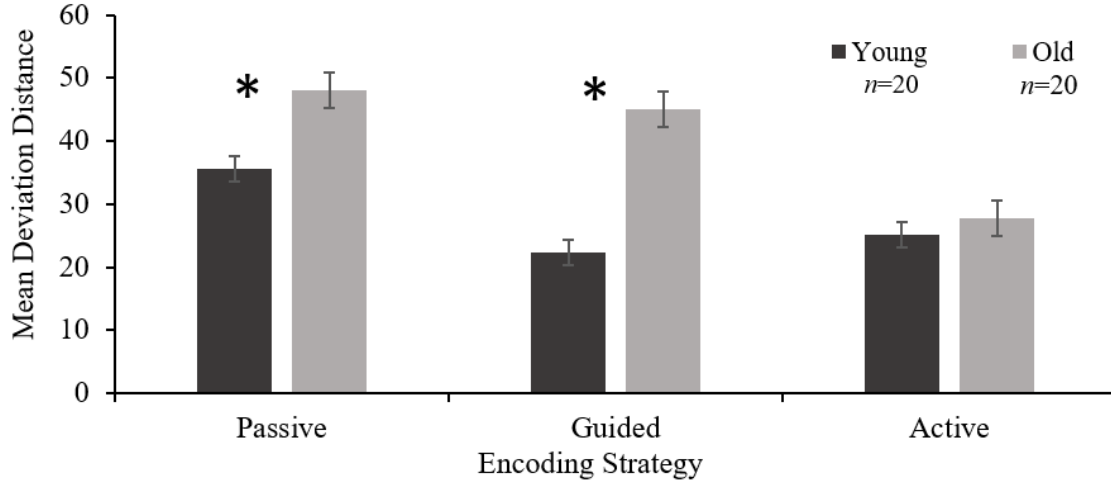
²Pattern of results replicate when conducting the ANOVA using the full sample of fifty-four younger participants.

³Bayes factors were calculated using the Bayes-Factor package in JASP, enlisting a default Jeffreys–Zellner–Siow (JZS) prior with a Cauchy distribution ($center = 0$, $r = 0.707$). This package compares the fit of various linear models. Bayes factor interpretations follow the conventions of Lee and Wagenmakers (2014). Bayes factors in favor of the alternative (BF_{10}) or null (BF_{01}) models are presented in accordance with each preceding report of null hypothesis significance testing analyses (i.e., based on a $p < .05$ criterion). A $BF_{10} > 1$ is interpreted as evidence in favour of the alternative hypothesis, while $BF_{01} > 1$ is interpreted as evidence in favour of the null.

$SE = 2.18$, $p = .483$, $BF_{01} = 3.43$, $d = 0.16$.

Older Group. I conducted another one-way repeated measures ANOVA to examine the effect of Navigation Condition on route overlap score as the dependent variable in the older group. There was a significant effect of Navigation, $F(2, 38) = 9.69$, $MSE = 218.11$, $p < .001$, $\eta_p^2 = 0.34$ (see Figure 12 for means). Paired sample t-tests showed that contrary to the younger group, older adults benefitted the most from active navigation (lower deviation value) relative to passive and guided exploration, $t(19) = -4.98$, $SE = 2.18$, $p < .001$, $BF_{10} = 325.80$, $d = -1.11$, and $t(19) = -2.98$, $SE = 2.18$, $p = .008$, $BF_{10} = 6.39$, $d = -0.67$, respectively. Notably, route deviation scores following passive and guided exploration did not differ, $t(19) = 1.30$, $SE = 2.18$, $p = .209$, $BF_{01} = 2.07$, $d = 0.29$. These findings show that active navigation enhanced route memory relative to guided and passive conditions in older adults. That I did not find a significant difference between passive and guided conditions suggests that motor engagement alone, present in the guided but not passive condition, is not sufficient to benefit route memory in older adults.

Figure 12. Route deviation in Passive, Guided, and Active conditions in younger and older adults.



Note. Lower deviation distance values indicate better memory for routes travelled. Error bars represent the standard error of the means. Asterisks represent group level significance at $p < .05$.

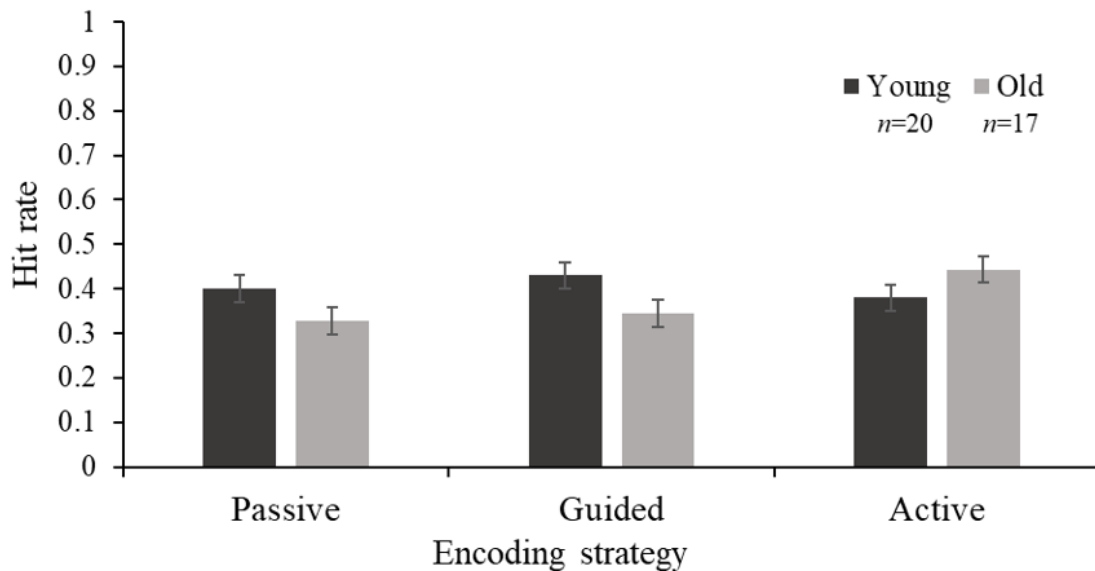
4.3.2 Landmark Memory Performance

I conducted a 2 (Group: Young vs Old) X 3 (Navigation Condition: Passive, Guided, and Active) mixed Analysis of Variance (ANOVA), with the first factor being between- and the second factor a within-subject manipulation, on landmark memory scores (i.e., Hit rates; see Figure 13 for means). For these analyses, I included only 17 older adults. This is because only those who completed all navigation trial types were permitted to complete the landmark memory assessment. The main effect of Navigation condition was non-significant, $F(2, 64) = 0.81$, $MSE = 0.01$, $p = .450$, $\eta_p^2 = 0.03$, as was the effect of Group, $F(1, 32) = 1.11$, $MSE = 0.04$, $p = .299$, $\eta_p^2 = 0.03$. We did, however, detect a significant Group X Navigation Condition interaction (see Figure 13), $F(2, 64) = 5.62$, $MSE = 0.01$, $p = .006$, $\eta_p^2 = 0.15$. To understand the interaction, I conducted separate one-way ANOVAs for each Group.

Younger Group. I conducted a one-way repeated measures ANOVA to examine the effect of Navigation condition on landmark memory score as the dependent variable. There was no significant effect of Navigation , $F(2, 38) = 0.49$, $MSE = 0.02$, $p = .614$, $\eta_p^2 = 0.03$ (see Figure 13 for means).

Older Group. Another one-way repeated measures ANOVA was conducted to examine the effect of Navigation condition on landmark memory in the older Group (see Figure 13 for means). There was a significant effect of Navigation, $F(2, 32) = 8.51$, $MSE = 0.01$, $p = .001$, $\eta_p^2 = 0.35$. Similar to the pattern of results observed for route memory, here too older adults benefitted the most from Active navigation relative to Passive and Guided exploration, $t(16) = 3.35$, $SE = 0.16$, $p = .010$, $BF_{10} = 54.07$, $d = 0.71$, and $t(16) = 2.94$, $SE = 0.03$, $p = .004$, $BF_{10} = 3.64$, $d = 0.81$, respectively. Notably, landmark memory was similar following guided and passive exploration, $t(16) = 0.76$, $SE = 0.16$, $p = .457$, $BF_{01} = 3.26$, $d = 0.19$.

Figure 13. Memory for landmarks (measured by hit rates for targets correctly recognized following encoding; false alarm rate for younger adults: 0.18; false alarm rate for older adults: 0.14) contained within environments explored using Passive, Guided, and Active navigation conditions in younger and older adults.



Note. Error bars represent the standard error of the means.

4.3.3 Assessment of Path Complexity

I examined whether taking a longer route during encoding (reflecting the topographical properties of the environment) could have influenced route memory. I computed a measure of path complexity for each route taken at encoding. I applied an angle-based measure (see Appendix for a detailed description of the equation) to quantify turns taken while exploring each environment. That is, I recorded each participant's position within each environment, at each 1 second time-point during their 40-second exploration. I then derived displacement vectors between positions at each consecutive time-point. Next, I calculated the angle between each pair of consecutive displacement vectors and normalized these angles to represent a complexity score between 0 and 1, such that a 0-degree turn (straight path) has a complexity of 0, and a 90-degree turn or greater has a complexity of 1. Finally, I summed each individual turn complexity score and divided by the total number of scores to calculate the average, representing the overall path complexity as a percentage for each environment (12 environments in total, with 4 for each navigation condition). For each navigation condition, I then computed the average path complexity score by averaging the scores across the four environments within that condition. This process was repeated for all participants in both age groups.

I conducted a 2 (Age: Young Vs Old) X 3 (Navigation Condition: Passive, Guided, Active) mixed ANOVA, with the first factor being between and the second factor a within-subject manipulation, on Path Complexity scores. The main effect of Navigation condition was not significant, $F(1.5, 52.52) = 0.50$, $MSE = 0.002$, $p = .559$, $\eta_p^2 = 0.01$, indicating that overall path complexity did not vary across the three navigation conditions⁴. However, there was a significant main effect of Age group, $F(1, 35) = 12.28$, $MSE = 0.003$, $p = .001$, $\eta_p^2 = 0.26$; path complexity was higher among younger ($M = 10.8\%$, $SD = 0.03$) relative to older adults ($M = 7.2\%$, $SD = 0.06$). Additionally, the Navigation condition X Age group interaction was also significant, $F(1.5, 52.52) = 5.01$, $MSE = 0.009$, $p = .017$, $\eta_p^2 = 0.13$. In the younger adults' group ($n = 20$), the effect of Navigation condition was non-significant, $F(1.36, 25.75) = 2.45$, $MSE = 0.02$, $p = .121$, $\eta_p^2 = 0.11$. In the older sample ($n = 17$), we found a significant effect of Navigation condition on path complexity, $F(1.34, 21.48) = 4.78$, $MSE = 8.33$, $p = .031$, $\eta_p^2 = 0.23$. Path complexity was higher in the passive ($M = 8.7\%$; $SD = 0.03$) than active condition ($M = 6.3\%$; $SD = 0.04$), $t(16) = 1.50$, $SE = 0.28$, $p = .024$, Cohen's $d = 0.61$, though no differences were observed between the passive and guided conditions ($M = 6.8\%$, $SD = 0.04$), $t(16) = 2.03$, $SE = 0.49$, $p = 0.059$, Cohen's

⁴Similar to the landmark analyses, here we included 17 older adults and 20 younger adults with complete data to account for path complexity. Mauchly's test indicated that the assumption of sphericity had been violated ($p < .05$) thus; a Greenhouse-Geisser correction was applied.

$d = 0.49$, nor between the Active and Guided conditions, $t(16) = -1.01$, $SE = 0.12$, $p = 0.329$, Cohen's $d = -0.24$.

Correlation analyses revealed no significant relationship between Active [$r(35) = 0.12$, $p = .484$], Guided [$r(35) = -0.15$, $p = .391$], and Passive [$r(35) = 0.02$, $p = .918$] path complexity and route memory performance⁵. These results provide strong evidence that the length of the route taken during encoding, reflecting the topographical properties of the environment and detours, did not influence route memory.

4.3.4 Self-reported Motivation

I conducted a 2 (Group: Young vs. Old) X 3 (Navigation Condition: Passive, Guided, and Active) mixed ANOVA, with the first factor being between- and the second factor a within-subject manipulation, on self-reported Motivation. There was a main effect of Navigation condition, $F(2, 76) = 15.65$, $MSE = 1.52$, $p < .001$, $\eta_p^2 = 0.29$, with higher motivation following the Active relative to Guided, $t(38) = 3.45$, $SE = 0.28$, $p = .003$, $d = 0.65$, and Passive conditions, $t(38) = 5.54$, $SE = 0.28$, $p < .001$, $d = 1.04$. There was no significant difference between Passive and Guided conditions, $t(38) = -2.09$, $SE = 0.28$, $p = .120$, $d = -0.39$. The effect of Group was also non-significant, $F(1, 38) = 0.55$, $MSE = 3.40$, $p = .462$, $\eta_p^2 = 0.01$, as was the Navigation Condition X Group interaction (see Table 4 for descriptives), $F(2, 76) = 2.42$, $MSE = 1.52$, $p = .095$, $\eta_p^2 = 0.02$.

4.3.5 Self-reported Preference

I conducted a 2 (Group: Desktop-VR vs Headset-VR) X 3 (Navigation Condition: Passive, Guided, and Active) mixed ANOVA, with the first factor being between- and the second factor a within-subject manipulation, on self-reported Preference. There was a main effect of Navigation condition, $F(2, 76) = 14.55$, $MSE = 2.33$, $p < .001$, $\eta_p^2 = 0.28$. Overall, preference was higher following active ($M = 5.88$, $SD = 1.08$) relative to guided ($M = 4.50$, $SD = 1.68$), $t(38) = 4.03$, $SE = 0.34$, $p < .001$, $d = 0.89$, and passive conditions ($M = 4.13$, $SD = 1.75$), $t(38) = 5.12$, $SE = 0.34$, $p < .001$, $d = 1.14$, though there was no difference between passive and guided conditions, $t(38) = -1.10$, $SE = 0.34$, $p = .827$, $d = -0.24$. The effect of Group was non-significant, $F(1, 38) = 0.67$, $MSE = 2.45$, $p = .419$, $\eta_p^2 = 0.03$, as was the Navigation condition X Group interaction (see Table 4 for descriptives), $F(2, 76) = 1.01$, $MSE = 2.33$, $p = .369$, $\eta_p^2 = 0.02$.

⁵Pearson correlation analyses were collapsed across Group (Younger and Older adults).

Table 4.

Mean motivation and preference scores in each Age group, following each navigation condition.

Standard deviation in parentheses.

Group and Condition	Motivation	Preference
Younger Adults		
Passive	4.20 (1.67)	4.45 (1.76)
Guided	4.40 (1.73)	4.35 (1.90)
Active	5.95 (1.32)	6.05 (1.23)
Older Adults		
Passive	4.35 (1.79)	3.80 (1.74)
Guided	5.30 (1.13)	4.65 (1.46)
Active	5.65 (0.93)	5.70 (0.92)

4.3.6 Predictors of Route Memory Performance

A forward stepwise regression analysis was conducted (collapsed across younger and older adults) to identify the strongest predictors of route memory performance⁶. I included the following measures in our model, as predictors: intersections crossed at encoding, number of stops within intersections, distance travelled, total time spent within an intersection, path complexity, motivation, preference, scores on the *Santa Barbara Sense of Direction Scale* (*SBSODS*), the *Igroup Presence Questionnaire* (*IPQ*), the *Simulator Sickness Questionnaire* (*SSQ*), and the *Five-Dimensional Curiosity Scale* (*5DC*). For the Active condition, the final model was statistically significant, $F(1, 70) = 5.59$, $p = .006$, and explained approximately 12% of the variance in route memory performance (adjusted $R^2 = .116$). We found that only the number of intersections crossed at encoding significantly predicted route memory performance, $\beta = -4.30$, $t = -2.32$, $SE = 1.85$, $p = .023$. This means that a one-unit increase in the intersections crossed at encoding leads to a 4.30 decrease in deviation distance (better memory).

⁶We used the complete sample of fifty-four younger adults and twenty older adults for the regression analyses.

For the Guided condition, a similar stepwise regression analysis was performed. However, no variables met the criteria for inclusion in the final model. As a result, the model did not include any predictors, and the variance explained was effectively zero ($R^2 = .00$).

For the Passive condition, the final model was statistically significant, $F(1, 70) = 3.99$, $p = .049$, and explained approximately 4% of the variance in route memory performance (adjusted $R^2 = .039$). I found that only the ‘joyous exploration’ subscale of the *5DC* curiosity questionnaire significantly predicted route memory performance, $\beta = -4.86$, $t = -1.99$, $SE = 2.43$, $p = .049$. This means that a one-unit increase in the joyous exploration measure leads to a 4.86 decrease in deviation distance (better memory).

4.4 Discussion

In Experiment 3, I manipulated the level of motor engagement and decision-making during exploration, and examined how these influenced memory for routes taken, and landmarks contained within VR environments, in younger versus older adults. Results revealed a clear age-related dissociation in the cognitive mechanisms that support route memory. Specifically, younger adults benefited equally from active and guided navigation strategies during encoding, while older adults showed significantly enhanced route and landmark memory only following the active navigation condition. These findings underscore the critical role of decision-making and agency in supporting spatial memory among older adult populations. In contrast, motor-based strategies are sufficient to boost performance in younger adults. These results carry broad implications for cognitive aging research, GPS implementation, and memory rehabilitation strategies. They highlight the importance of aligning navigation interventions with age-specific considerations.

4.4.1 Neural Mechanisms in Younger Adults: The Role of Motor Engagement

Younger adults in the current study benefited similarly from active and guided navigation during encoding of an environment. This finding aligns with prior research that has shown the importance of motor engagement on memory for routes in this population (Sivashankar et al., 2024; Sivashankar & Fernandes, 2025). Specifically, past studies have highlighted that motor cues—such as vestibular, proprioceptive, and visual feedback—are integral for encoding spatial information (Sivashankar et al., 2024; Chrastil & Warren, 2012). These

sensory-motor cues likely support egocentric representations of space by reinforcing the physical actions associated with turning, orienting, and moving through an environment.

I suggest that the intact sensory-motor systems of younger adults allow them to effectively process and integrate inertial cues, enhancing spatial updating and route retention. This capacity makes the act of movement—whether self-directed or externally guided—an effective mechanism for supporting memory. The involvement of basal ganglia structures, such as the caudate nucleus, which are implicated in procedural and habit learning (Hartley et al., 2003), may further explain the benefit observed in our guided navigation condition, even when decision-making was externally removed. This may have occurred because route memory is a form of procedural habit formation, involving stimulus-response associations (Wiener et al., 2012). Even during guided navigation, participants were able to form such place-action associations, which later enhance retention.

Route memory involves sequences of decisions, such as "go straight, turn right, then turn left," which require specific actions at key intersections (Ruddle et al., 2011). Since participants were tasked with retracing the exact route during retrieval, their memory likely relied on the striatal regions, which are involved in recalling sequences of actions (Burgess, 2008). Although the guided condition eliminated the need for decision-making, it still provided participants with sufficient inertial cues, including proprioceptive, vestibular, and visual flow information (Smith, 2017; Waller et al., 2004; Zhu et al., 2022). I believe participants used these cues later to retrieve the exact route taken during encoding. A notable finding from my data is that route memory performance in the guided condition differed significantly from that in the passive condition (specifically in the younger group). This suggests that the motor information provided during guided exploration was sufficient to enhance memory, compared to passive exploration. Importantly, I argue that when motor functions are diminished in older adults (Ward and Frackowiak, 2003), they must increasingly rely on active decision-making skills to support spatial memory. This shift in reliance may reflect a compensatory mechanism (Burgess, 2008), where engaging in intentional and effortful choices about where to go and how to navigate helps offset declines in procedural aspects of route learning that are typically supported by motor engagement. In short, motor engagement at encoding is both necessary and sufficient for enhancing route knowledge in younger adults.

4.4.2 Neural Mechanisms in Older Adults: The Importance of Agency

In contrast, older adults in this study showed enhanced route and landmark memory only when they were actively engaged in decision-making during navigation (active condition). There was no difference in performance in the guided relative to passive navigation condition in this group, despite the former engaging motor functions during encoding. I suggest that motor engagement is insufficient on its own to support spatial memory in aging populations. Notably, there were no age-related differences in route or landmark memory following Active navigation suggesting that this is a strategy that mitigates age-related declines in performance. Importantly, If the poorer performance in the Guided condition were primarily due to anxiety or cognitive load from following the line, then older adults should have shown comparable benefits in the Passive and Active conditions—since Passive navigation removes the pressure to adhere to a path, and Active navigation allows full autonomy. However, the results clearly show that older adults exhibit the strongest route and landmark memory following Active navigation, and that the presence of motor cues in the Guided condition does not provide a comparable advantage over Passive viewing. These patterns suggest that, for older adults, it is the combination of self-directed movement and active decision-making that drives improvements in spatial memory.

Aging is associated with pronounced cortical atrophy in the frontal and medial temporal lobe structures such as the hippocampus (Buckner, 2004; Konishi & Bohbot, 2013). The frontal lobes and hippocampus play a central role in allocentric navigation, which involves integrating environmental cues and forming cognitive maps (Burgess, 2008). These areas are also vital for executive functions such as decision-making, working memory, and cognitive flexibility. For older adults, active navigation—which requires decision-making at key decision points—engages the prefrontal cortex, an area associated with executive control (Preston & Eichenbaum, 2013) and agency (Vinogradov et al., 2006). In contrast, passive or guided navigation eliminates the need for decision-making. When older participants are given the opportunity to actively engage with their environment, with agency and independent decision-making, they appear to experience enhanced encoding, resulting in better subsequent memory. Supporting this claim, findings by Lockhart and colleagues (2012) highlight the critical role of the prefrontal cortex and hippocampus in successful navigation and memory among older adults. The prefrontal cortex supports intentional memory, and during active navigation, older adults are specifically required to engage in goal-directed exploration to locate the "gold star" as the destination. This differs to the guided condition, where they simply follow visual cues overlaid on the path to reach the destination. I propose that the heightened cognitive demands placed on the prefrontal

cortex during active navigation may help offset age-related declines in the spontaneous engagement of these neural regions. This, in turn, may facilitate better integration of spatial and contextual information. Furthermore, older adults often experience motor deficits, such as reduced fine motor control, slower reaction times, and difficulty with coordination and balance, all of which can hinder navigation performance. As a result, older adults may not rely as heavily on motor engagement to remember routes travelled, making it even more important to engage the frontal lobes through active decision-making during encoding (Sul et al., 2010). My findings support the notion that engagement of executive functions and a sense of agency, rather than motor activity alone, is the critical factor underlying improvements in route memory among older adults.

Beyond route memory performance, I also observed a similar pattern of findings for landmark memory among older adults. This further supports the idea that decision-making strategies engaged during active exploration can enhance an individual’s ability to retrieve environmental cues that aid navigation. The absence of this pattern in younger adults may be due to age-related differences in focus of attention during exploration. For example, past research suggests that older adults are more likely than younger adults to actively seek out cues that can help anchor them in space (Anderson & Craik, 2017; Fricke et al., 2002). This could explain why we observed a benefit from the active condition on landmark memory in older adults, but not in younger adults.

4.4.3 A Role for Individual Differences in Spatial Memory

In both younger and older adults, active navigation was associated with the highest self-reported motivation, which supports the notion that more engaging navigation strategies, particularly those involving decision-making and motor engagement, are perceived as more motivating (Sauzéon et al., 2016). In contrast, motivation was significantly lower in the passive condition, which lacked such engagement. These findings are consistent with the notion that active engagement with the environment promotes greater motivation and memory retention, particularly for older adults (Preston & Eichenbaum, 2013). These results also directly replicate my previous findings in younger adults when assessing route memory (Sivashankar et al., 2024; Sivashankar et al., 2025). Although we observed differences in motivation and preference ratings between conditions in both age groups, these subjective measures did not emerge as significant predictors of memory performance. This finding suggests that affective responses such as how enjoyable or engaging participants found a navigation condition does not necessarily reflect the navigational learning acquired by the participant. The poor predictive value of motivation and preference underscores the distinction between subjective experience and the objective demands of spatial memory.

In terms of predictors of route memory performance, intersections crossed at encoding significantly predicted route memory in the active condition in both age groups. These results align with prior animal research indicating that intersections serve as salient spatial boundaries, helping to contextualize cognitive maps (Moser et al., 2008). In the Passive condition, only the joyous exploration subscale from the Five-Dimensional Curiosity Scale was a significant predictor, suggesting that curiosity-driven motivation plays a role in memory performance when navigation is passive.

4.4.4 Conclusion

The current research makes an important contribution to the growing literature on the differential roles of motor and executive functions in spatial memory (Chrastil & Warren, 2012; Jebara et al., 2014). Our findings provide empirical support for the hypothesis that age-related memory deficits can be mitigated through task design; specifically by engaging decision-making capacities. While younger adults gain a memory benefit from motor engagement alone, older adults require cognitive demands or challenges that more actively engage independent decision-making, to benefit retention of routes and landmarks.

The use of VR technology allowed for manipulation of both motor and cognitive demands, providing a controlled environment that would be difficult to replicate in real-world settings. This methodological approach ensured that the observed effects were due to the experimental conditions rather than individual differences in baseline spatial ability or motivation. Furthermore, our within-subject design helped to isolate the effects of navigation strategy on spatial memory, while controlling for any confounding variables such as structural differences in environment simulation, speed, and path complexity.

In conclusion, the current Experiment suggests that adapting navigation strategies to match the cognitive strengths of each age group, by focusing on motor activity in younger adults and on decision making in older adults, may be a promising approach to improving spatial memory. Our findings have implications for the design of assistive technologies, urban planning, and cognitive interventions aimed at supporting cognitive health across the lifespan. Allowing opportunities for independent decision-making can help mitigate age-related declines and better support spatial memory in later life.

Chapter 5

General Discussion

Route memory requires the successful retrieval of place information and specific action sequences at identifiable locations or decision points (Appleyard, 1970; O'Malley, 2018). The use of navigation aids such as the Global Positioning System GPS has significantly improved travel efficiency by enabling users to reliably navigate between points, take shortcuts, and reroute in the presence of road closures. However, dependence on GPS limits an individual's need to make independent decisions about the path of travel. While some studies have reported negative effects of GPS use on memory (Dahmani & Bohbot, 2020; Gardony et al., 2013), specifically on global configural map knowledge¹, its impact on other aspects of spatial cognition such as route knowledge and landmark memory remain unexplored (Chrastil & Warren, 2015). It is especially important to investigate the impact of GPS-type guided navigation on spatial memory in older adults who a) may find this technology foreign, and b) typically have brain-related changes in key motor and memory regions involved in navigation, (Buckner, 2004; Konishi & Bohbot, 2013) that may limit its usefulness. As well, as the young adult population ages, it will be important to determine whether any observed benefits from GPS are sustained into older adulthood.

To this end, this dissertation investigated the cognitive mechanisms supporting spatial memory through three VR-based experiments, focusing on the relative contributions of motor engagement and decision-making during navigation. Across three experiments, my findings demonstrated that while younger adults benefited from motor engagement during navigation, older adults required active decision-making to sustain route and landmark

¹Configural map knowledge consists of an integrated mental representation of all roads and landmarks encompassing an environment (i.e., a cognitive map), thus reflecting global knowledge for the environment explored (Chrastil & Warren, 2013).

memory. Guided navigation, despite involving motor activity, did not provide memory benefits for older adults, highlighting the central role of decision-making in supporting spatial memory in aging. These findings advance our understanding of how navigation strategies interact with cognitive aging, underscoring the need to consider both technological reliance and neural changes when evaluating spatial memory. Looking forward, this work points to the potential of cognitive interventions that deliberately engage decision-making processes as a way to maintain spatial memory in older adulthood and in populations at risk of cognitive decline. Together, these studies provide new insights into how navigation strategies shape route and landmark memory, and how these processes differ across the lifespan.

5.1 Motion Cues as a Foundation for Route Memory

Converging evidence from all three experiments showed that in younger adults, decision-making about the path of travel at encoding did not confer a benefit to route memory, more than that conferred by motoric engagement. In the domain of spatial navigation, route memory has been shown to recruit the use of vestibular and proprioceptive cues from head and body rotation to aid formation of an internal spatial representation of an explored environment (Jabbari, 2022). Precisely, past work has reported two distinct critical sources of information that humans rely on when navigating: these include landmark cues originating from the external environment, and self-motion cues stemming from body movement (Jabbari, 2022). In the context of self-motion cues, the vestibular system, which includes the semicircular canals of the inner ear, transduces inertial cues arising from physical motion, and is regarded as critical to spatial orientation (Day & Fitzpatrick, 2005; Smith, 2017).

I suspect that for one to successfully reproduce a route previously travelled, they would require continuous integration of body-based self-motion cues from the visual, vestibular and proprioceptive systems (Chrastil and Warren, 2012; see Cullen & Taube, 2017 for review). For example, continuous and sequential visual information received by the retina informs people about the flow of passing stimuli (i.e., optic flow) and helps one to perceive movement in space (Jabbari, 2022), while both vestibular and proprioceptive systems provide information about position of limbs in space during self-generated movement (Waller et al., 2004; Cullen & Taube, 2017). In addition, recent work by Zhu and colleagues (2022) examined eye movements and found that participants made greater saccades forward and backward along the intended path of travel (i.e., the path containing the reward). Critically, the number of sweeping eye movements increased with environmental complexity. These findings suggest that eye movements guide one’s movement in space in a goal-directed manner, rather than in a bottom-up process that is purely driven by the

saliency of a stimulus (Zhu et al., 2002). In relation to the findings of the current study, both active and guided navigation required the integration of oculomotor, vestibular and proprioceptive systems to guide eye movements and motion towards the path of travel. That is, one had to direct their gaze and orient their head, body, and the position of the VR controller towards a desired path to move in that direction. The failure to accurately carry out any one of these steps described above would prevent one from travelling in the desired direction. During passive navigation, however, one did not have to carry out a sequence of integrated self-generated motion involving gaze control, face and body rotation, as there was no motion required by the participant to move in passive exploration. Given that route memory was lowest in this condition, it appears that this factor is particularly important in explaining any boost to performance.

Moreover, work in mice and humans has shown the importance of context reinstatement to spatial navigation. Context reinstatement refers to the finding that in grid and place cells of the medial entorhinal cortex and hippocampus (respectively), the spatial and temporal attributes of a space at encoding are reinstated (i.e., firing patterns) just before retrieval (Lewis & Durrant, 2011; Jacobs et al., 2013)². For example, we know from past work that place cells in the hippocampus do not show the same firing pattern in all locations that are perceptually identical to one another (Sharp, 1999). Rather, hippocampal place cells receive inputs from vestibular, proprioceptive systems, and visual motion to distinguish locations as A and B in order to modify patterns of cell firing (see Moser et al., 2008 for review). In this experiment, encoding and retrieval for any given city occurred in the same environment, and the subsequent retrieval phase required one to reproduce the path taken at encoding. From past work, we know that place cells use both visual and motor cues to reconstruct a spatial map of an explored environment (see Moser et al., 2008 for review). Given this, I speculate there must be a reinstatement of place cell firing at retrieval that is reflective of the motor activity engaged at encoding. This along with the visual cues in the form of landmarks (Jabbari et al., 2022), is believed to explain the benefit to route memory in both active and guided navigation. Based on these results, I suggest that engagement of motoric processing during initial navigation is particularly potent in enhancing route memory.

²Place cells in the hippocampus encodes specific locations in space, whereas grid cells in the medial entorhinal cortex fire in response to spaces that represent a grid-like pattern (see Moser et al., 2008 for review).

5.2 The Importance of Type of Retrieval Test

In all three Experiments, I asked participants to reproduce the path taken at encoding, thus, I utilized a motor-based memory test that likely engaged the same processes as at encoding. In the past, researchers have used map drawing, landmark recognition, and pointing accuracy to target objects, to determine the relative contribution of decision-making and motor processing to spatial memory (Gardony et al., 2013; Munzer et al., 2006; Von Stülpnagel & Steffens, 2012; see Chrastil & Warren, 2012 for review). These studies have suggested that decision-making is superior to motor control in terms of improving spatial performance. In instances where survey knowledge is examined, it is indeed possible that the requirement to follow explicit instructions given by a GPS during guided navigation would divide attention, and impair memory on such global memory tests (e.g., on map drawings). In fact, Gardony and colleagues (2013) suggest that it is precisely attention that is impaired in the presence of guided navigation that limits performance on global knowledge tests, as participants need to hold instructions in working memory and navigate, thereby, failing to attend to landmarks and other routes making up an environment³.

Further, Chrastil and Warren (2015) found that decision-making is an integral component in acquiring topological graph knowledge, where one must know the various connecting routes of an environment to be able to detour and take novel routes to reach a target at test. Route memory on the other hand is a test in which one must remember particular action sequences at specific locations within a route (see Chrastil & Warren, 2012 for review). Hence, it is possible to remember specific turns solely based on one's initial motoric or procedural memory for the paths taken. In light of our findings, I suggest that self-generated movements are a critical component to enhancing memory for spatial routes, more so than decision-making about the path of travel; our results, however, might only apply when the assessment of memory involves 'reproducing' one's steps. Future work should consider whether guided navigation at encoding would provide less benefit when the assessment of memory is more conceptual or requires topographical knowledge.

Regardless, based on these current findings, I claim that self-generated movements are a crucial factor in enhancing memory for spatial routes, potentially more so than decision-making about the travel path. However, it is important to note that these results may be limited to contexts in which memory assessment involves accurately reproducing one's steps (motor-based memory task). Future research should investigate whether guided navigation during encoding provides less benefit when the memory assessment requires

³Survey knowledge consists of an integrated mental representation of all roads and landmarks encompassing an environment (i.e., a cognitive map), thus reflecting global knowledge for the environment explored (Chrastil & Warren, 2013).

more conceptual or topographical knowledge. To this end, my future work is investigating the impact of guided navigation on various measures of survey-based spatial memory, in both younger and older adults, such as map drawings of routes traversed.

5.3 Decision-Making as a Key Determinant of Route and Landmark Memory in Aging

In the published work reported in Chapters 2 and 3, I showed that self-motion cues such as head rotations, full-body 360-degree turns, and forward movement via handheld controller during initial exploration of a virtual environment are sufficient to enhance route knowledge in younger adults (Sivashankar et al., 2024; Sivashankar & Fernandes, 2025). Specifically, I found that both guided navigation (analogous to following GPS instructions) and active exploration of cities during encoding provided comparable benefits to later route retrieval, despite the former limiting decision-making. However, it remained unclear whether this pattern holds for older adults.

Experiment 3 revealed that older adults in my study showed enhanced route and landmark memory only when they were actively engaged in decision-making during navigation (active condition). In contrast, there was no performance difference between the guided and passive conditions, despite the guided condition involving motor engagement during encoding. These findings suggest that decision-making plays a critical role in supporting spatial memory, particularly in populations where motor control may be diminished and motor cues less reliable. This aligns with Buckner’s (2004) review, which highlights that increased recruitment of the frontal lobes likely occurs as a compensatory response to age-related dysfunction, such as changes in the frontal-striatal or medial temporal systems. As task demands increase—whether through active exploration or in the context of pathological burden (e.g., Alzheimer’s disease)—compensatory mechanisms may be recruited to preserve aspects of cognitive function. In my future postdoctoral research, I aim to examine whether cognitive interventions that actively engage decision-making processes can help sustain spatial memory performance in aging populations and in those at risk of cognitive decline, such as individuals with amnesic mild cognitive impairment.

5.4 The Interplay between Individual Differences and Spatial Memory

Across three Experiments, my dissertation highlighted the role of individual differences in shaping spatial navigation performance in both immersive and non-immersive virtual environments. Specifically, I have shown that factors like motivation, preference, presence, and curiosity have the ability to shape spatial memory performance. Prior work has emphasized, for example, that individuals high in intrinsic motivation tend to engage more deeply with exploratory tasks, leading to stronger encoding and retrieval of spatial information (Sauzéon et al., 2016). Similarly, a stronger sense of presence in virtual environments has been linked to improved spatial learning, as participants who feel more immersed are more likely to treat the VR environment as analogous to real-world navigation (Sauzéon et al., 2016).

Personality factors like curiosity also play a critical role. Greater curiosity has been associated with enhanced memory and exploratory behavior, potentially through dopaminergic mechanisms that facilitate hippocampal-dependent learning (Gruber et al., 2014). My findings align with this literature by demonstrating that curiosity and related motivational states can amplify the memory benefits of active navigation, particularly when individuals are encouraged to explore and make decisions.

Results in Experiment 3 also showed that increased dwell time at key intersection points has the potential to decrease route deviation, thus resulting in better memory. This relationship highlights the importance of pausing at key decision points when following GPS directions. Stopping at intersections may enhance spatial memory by providing time to encode surrounding landmarks and spatial cues.

Taken together, these results highlight that navigation is not only influenced by the method we adopt at the time of exploration, but also by individual psychological traits. Recognizing these sources of variability is especially important for applied contexts such as designing cognitive interventions, VR training protocols, or assistive navigation technologies. Tailoring navigation strategies to account for motivation, presence, and curiosity may enhance engagement and improve spatial memory outcomes across different populations, including aging adults and those with cognitive impairments.

5.5 Future Directions

I recognize that experiencing VR environments while sitting down, as did the participants in this PhD thesis, limits the sensory and motor cues gained about one's location in space when exploring an unfamiliar environment, relative to walking. However, my research paradigm still allowed for participants to engage in motor actions to dictate the path of travel (i.e., to enable head and body rotation, and turning of the steering-wheel controller) and utilize vestibular information received from head rotation (see Chrastil and Warren, 2012 for review; Von Stülpnagel & Steffens, 2012). Further, seminal reviews and research in the field of spatial navigation have also manipulated motor control similarly (see Chrastil and Warren, 2012 for review; Chrastil and Warren, 2013; Stülpnagel & Steffens, 2012). Thus, I believe that my manipulation of motor control is one that sufficiently reflects current definitions of motor actions outlined by the field. Nonetheless, future studies could allow for greater motor engagement by having participants actually walk while immersed in VR to better simulate the inertial cues (i.e., cues that provide information about linear and angular acceleration) evoked when exploring new surroundings (Waller & Nadel, 2013). To more directly assess the role of motoric and decision-making contributions to spatial memory, a future study could compare passive, guided, and active navigation in real-world settings, such as having participants traverse the underground tunnels connecting university buildings. For instance, in the Guided condition participants could follow GPS-style directions to locate a target room, in the Active condition they could navigate independently to find the target room, and in the Passive condition they could watch a video of someone else completing the route. Such an in-person design would capture natural locomotion more accurately and strengthen the ecological validity and real-world generalizability of the findings. Studies should also directly measure head movements to determine whether a greater rotation of the head, indicative of visual observation, could influence subsequent spatial memory.

Another dependent variable to consider in future work, when examining the influence of navigation strategies on spatial memory performance, is roaming entropy. This is an index of the variability in an individual's territorial coverage, and it is demonstrated as a good measurement of participants' motivation during the study phase of VR (Cen et al., 2024). Future research could incorporate roaming entropy as an objective measure of exploration to assess whether higher entropy (i.e., exploration covering many zones within an environment) corresponds to increased curiosity and motivation, ultimately enhancing spatial memory performance. Including such measures would help disentangle the interplay between exploration strategies, motivation, and memory retention, adding an important dimension to our current findings.

Finally, I believe that it is also important to consider the authenticity of spatial environments when examining spatial memory. In the current work, I made considerable efforts to enhance ecological validity. I used virtual environments that mimic real-world streets, carefully designing street layouts and incorporating landmarks unique to each city (e.g., a red telephone booth in London). Environments were counterbalanced across participants, making it unlikely that structural differences between environments systematically influenced the results. Notably, very few previous studies examining route memory have incorporated such realistic urban simulations. Therefore, I believe that my approach provided a realistic estimate of navigational experience compared to typical VR paradigms. However, future research can further enhance the realism of virtual environments by including auditory features like sirens, car honks, and pedestrians, to mimic the complexity of real-world navigation.

5.6 Implications for Navigation Aids and Cognitive Training

The results of this research have implications for the design of navigation aids, especially for older adults. Current GPS systems and navigation tools automate route guidance, reducing the need for user decision-making. However, these features may inadvertently diminish cognitive engagement, particularly limiting opportunities for older users to engage their executive functions and strengthen their spatial memory (Gardony et al., 2013; Parush et al., 2007). Given this, the design of future GPS systems and navigation tools should be reconsidered to better align with the cognitive profiles of older adults. For example, systems that encourage decision-making, such as prompting users to choose between alternative routes could stimulate frontal-hippocampal networks and enhance memory for routes travelled (Shohamy & Daw, 2015; Shin et al., 2019). Even subtle modifications, like delaying guidance until the user attempts a decision, could introduce beneficial cognitive challenges that support later recall. In addition, the finding that motor engagement during encoding benefits route memory in younger adults suggests that self-driving cars, which reduce physical involvement, may impede the formation of spatial memory in this group. These results should be considered when developing policies related to driving practices and the design of future vehicles.

5.7 Conclusion

This dissertation has sought to determine whether the use of a navigational aid at encoding influenced spatial memory, and second, whether there were any differences in utility of different navigation strategies on route and landmark memory across younger and older adults. Across three Experiments, I have shown that while younger adults gain a memory benefit from motor engagement alone, older adults require cognitive demands or challenges that more actively engage independent decision-making, to benefit retention of routes and landmarks. By identifying distinct mechanisms that benefit younger and older adults, this work advances our theoretical understanding of spatial memory across the lifespan while also informing the development of age-sensitive navigational tools and strategies. My dissertation has also revealed the role of individual differences in shaping spatial navigation performance in both immersive and non-immersive virtual environments. That is, I have shown that measures like motivation, preference, and curiosity have the potential to enhance or reduce spatial memory performance. However, converging evidence across all three experiments indicates that the overall effect of navigation conditions cannot be outweighed by subjective measures of preference, motivation, or curiosity. Ultimately, these findings illustrate that the cognitive processes supporting spatial memory are not uniform across age groups, but instead depend on the interplay between motor engagement, decision-making, and the demands of the navigational context.

References

- Appleyard, D. (1970). Styles and methods of structuring a city. *Environment and behavior*, 2(1), 100-117.
- Anderson, N. D., & Craik, F. I. (2017). 50 years of cognitive aging theory. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 72(1), 1-6. <https://doi.org/10.1093/geronb/gbw108>
- Bakdash, J. Z., Linkenauger, S. A., & Proffitt, D. (2008, September). Comparing decision-making and control for learning a virtual environment: Backseat drivers learn where they are going. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 52, No. 27, pp. 2117-2121). Sage CA: Los Angeles, CA: SAGE Publications.
- Bampouni, E., Ahmad, A., Xi, N., Legaki, N. Z., & Hamari, J. (2024, October). Effects of Immersion and Embodiment on Memory in Virtual Reality. In Proceedings of the 27th International Academic Mindtrek Conference (pp. 58-67). doi: <https://doi.org/10.1145/3681716.3681724>
- Buckner, R. L. (2004). Memory and executive function in aging and AD: multiple factors that cause decline and reserve factors that compensate. *Neuron*, 44(1), 195-208. <https://doi.org/10.1196/annals.1440.002>
- Burgess, N. (2008). Spatial cognition and the brain. *Annals of the New York Academy of Sciences*, 1124(1), 77-97. doi: <https://doi.org/10.1196/annals.1440.002>
- Brunyé, T. T., Mahoney, C. R., Augustyn, J. S., & Taylor, H. A. (2009). Emotional state and local versus global spatial memory. *Acta psychologica*, 130(2), 138-146. doi: <https://doi.org/10.1016/j.actpsy.2008.11.002>
- Cabeza, R., Grady, C. L., Nyberg, L., McIntosh, A. R., Tulving, E., Kapur, S., ... & Craik, F. I. (1997). Age-related differences in neural activity during memory encoding and retrieval: a positron emission tomography study. *Journal of neuroscience*, 17(1), 391-400. <https://doi.org/10.1523/JNEUROSCI.17-01-00391.1997>
- Cabeza, R., Anderson, N. D., Locantore, J. K., & McIntosh, A. R. (2002). Aging gracefully: compensatory brain activity in high-performing older adults. *Neuroimage*, 17(3), 1394-1402. <https://doi.org/10.1006/nimg.2002.1280>

- Carassa, A., Geminiani, G., Morganti, F., & Varotto, D. (2002). Active and passive spatial learning in a complex virtual environment: The effect of efficient exploration. *Cognitive processing*, 3(4), 65-81.
- Cen, D., Teichert, E., Hodgetts, C. J., & Gruber, M. J. (2024). Curiosity shapes spatial exploration and cognitive map formation in humans. *Communications Psychology*, 2(1), 129. doi: 10.1038/s44271-024-00174-6
- Chen, C. (2000). Individual differences in a spatial-semantic virtual environment. *Journal of the American society for information science*, 51(6), 529-542.
- Chrastil, E. R., & Warren, W. H. (2012). Active and passive contributions to spatial learning. *Psychonomic bulletin & review*, 19(1), 1-23. <https://doi.org/10.3758/s13423-011-0182-x>
- Chrastil, E. R., & Warren, W. H. (2013). Active and passive spatial learning in human navigation: acquisition of survey knowledge. *Journal of experimental psychology: learning, memory, and cognition*, 39(5), 1520. <https://doi.org/10.1037/a0032382>
- Chrastil, E. R., & Warren, W. H. (2015). Active and passive spatial learning in human navigation: acquisition of graph knowledge. *Journal of experimental psychology: learning, memory, and cognition*, 41(4), 1162. doi: 10.1037/xlm0000082
- Coto, J., Alvarez, C. L., Cejas, I., Colbert, B. M., Levin, B. E., Huppert, J., ... & Liu, X. Z. (2021). Peripheral vestibular system: Age-related vestibular loss and associated deficits. *Journal of otology*, 16(4), 258-265. <https://doi.org/10.1016/j.joto.2021.06.001>
- Cullen, K. E., & Taube, J. S. (2017). Our sense of direction: progress, controversies and challenges. *Nature neuroscience*, 20(11), 1465-1473. <https://doi.org/10.1038/nn.4658>
- Dahmani, L., & Bohbot, V. D. (2020). Habitual use of GPS negatively impacts spatial memory during self-guided navigation. *Scientific reports*, 10(1), 6310. <https://doi.org/10.1038/s41598-020-62877-0>
- Daselaar, S., Veltman, D. J., Rombouts, S. A. R. B., Raaijmakers, J. G. W., & Jonker, C. (2003). Neuroanatomical correlates of episodic encoding and retrieval in young and elderly subjects. *Brain*, 126(1), 43-56. <https://doi.org/10.1093/brain/awg005>
- Day, B. L., & Fitzpatrick, R. C. (2005). The vestibular system. *Current biology*, 15(15), 583-586. <https://doi.org/10.1113/jphysiol.2005.092544>

- Epstein, R. A., Patai, E. Z., Julian, J. B., & Spiers, H. J. (2017). The cognitive map in humans: spatial navigation and beyond. *Nature neuroscience*, *20*(11), 1504-1513. doi: 10.1038/nn.4656
- Euston, D. R., Gruber, A. J., & McNaughton, B. L. (2012). The role of medial prefrontal cortex in memory and decision making. *Neuron*, *76*, 1057 – 1070. [https : //doi.org/10.1016/j.neuron.2012.12.002](https://doi.org/10.1016/j.neuron.2012.12.002)
- Farrell, M. J., Arnold, P., Pettifer, S., Adams, J., Graham, T., & MacManamon, M. (2003). Transfer of route learning from virtual to real environments. *Journal of Experimental Psychology: Applied*, *9*, 219–227. doi:10.1037/1076-898X.9.4.219
- Field, A. P. (2005). Is the meta-analysis of correlation coefficients accurate when population correlations vary?. *Psychological methods*, *10*(4), 444.
- Fricke, M., Morawietz, C., Wunderlich, A., Muehlbauer, T., Jansen, C. P., Gramann, K., & Wollesen, B. (2022). Successful wayfinding in age: A scoping review on spatial navigation training in healthy older adults. *Frontiers in psychology*, *13*, 867987. [https : //doi.org/10.3389/fpsyg.2022.867987](https://doi.org/10.3389/fpsyg.2022.867987)
- Frissen, I., Campos, J. L., Souman, J. L., & Ernst, M. O. (2011). Integration of vestibular and proprioceptive signals for spatial updating. *Experimental brain research*, *212*, 163-176. doi: 10.1007/s00221-011-2717-9
- Gardony, A. L., Brunyé, T. T., Mahoney, C. R., Taylor, H. A. (2013). How navigational aids impair spatial memory: Evidence for divided attention. *Spatial Cognition & Computation*, *13*(4), 319-350. [https : //doi.org/10.1080/13875868.2013.792821](https://doi.org/10.1080/13875868.2013.792821)
- Gaunet, F., Vidal, M., Kemeny, A., & Berthoz, A. (2001). Active, passive and snapshot exploration in a virtual environment: Influence on scene memory, reorientation and path memory. *Cognitive brain research*, *11*(3), 409-420. [https://doi.org/10.1016/S0926-6410\(01\)00013-1](https://doi.org/10.1016/S0926-6410(01)00013-1)
- Grady, C. L., McIntosh, A. R., Horwitz, B., Maisog, J. M., Ungerleider, L. G., Mentis, M. J., ... & Haxby, J. V. (1995). Age-related reductions in human recognition memory due to impaired encoding. *Science*, *269*(5221), 218-221. doi: 10.1126/science.7618082
- Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). Article States of Curiosity Modulate Hippocampus-Dependent Learning via the Dopaminergic Circuit. *Neuron*, *84*(2), 486–496. [https : //doi.org/10.1016/j.neuron.2014.08.060](https://doi.org/10.1016/j.neuron.2014.08.060)

- Gruber, M. J., & Ranganath, C. (2019). How curiosity enhances hippocampus-dependent memory: The prediction, appraisal, curiosity, and exploration (PACE) framework. *Trends in cognitive sciences*, 23(12), 1014-1025. doi: 10.1016/j.tics.2019.10.003
- Gutchess, A. H., Welsh, R. C., Hedden, T., Bangert, A., Minear, M., Liu, L. L., & Park, D. C. (2005). Aging and the neural correlates of successful picture encoding: frontal activations compensate for decreased medial-temporal activity. *Journal of cognitive neuroscience*, 17(1), 84-96. <https://doi.org/10.1162/0898929052880048>
- Harris, M. A., & Wolbers, T. (2014). How age-related strategy switching deficits affect wayfinding in complex environments. *Neurobiology of aging*, 35(5), 1095-1102. <https://doi.org/10.1016/j.neurobiolaging.2013.10.086>
- Hartley, T., Maguire, E. A., Spiers, H. J., & Burgess, N. (2003). The well-worn route and the path less traveled: distinct neural bases of route following and wayfinding in humans. *Neuron*, 37(5), 877-888. 10.1016/S0896-6273(03)00095-3
- Hayes, A. F. (2018). An Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach (2nd ed.). New York: Guilford Press.
- Hegarty, M., Montello, D. R., Richardson, A. E., Ishikawa, T., & Lovelace, K. (2006). Spatial abilities at different scales: Individual differences in aptitude-test performance and spatial-layout learning. *Intelligence*, 34(2), 151-176.
- Hon, N., & Yeo, N. (2021). Having a sense of agency can improve memory. *Psychonomic Bulletin & Review*, 28, 946-952. doi: 10.3758/s13423-020-01849-x
- Ishikawa, T. (2019). Satellite navigation and geospatial awareness: Long-term effects of using navigation tools on wayfinding and spatial orientation. *The Professional Geographer*, 71(2), 197-209
- Jabbari, Y. (2022). Route Navigation and Driving: Role of Visual Cues, Vestibular Cues, Visual Spatial Abilities, Age and Mood Disorders (Doctoral dissertation).
- Jabbari, Y., Kenney, D. M., von Mohrenschildt, M., & Shedden, J. M. (2021). Vestibular cues improve landmark-based route navigation: A simulated driving study. *Memory & Cognition*, 49(8), 1633-1644.
- Jacobs, J., Weidemann, C. T., Miller, J. F., Solway, A., Burke, J. F., Wei, X. X., ... & Kahana, M. J. (2013). Direct recordings of grid-like neuronal activity in human spatial navigation. *Nature neuroscience*, 16(9), 1188-1190. <https://doi.org/10.1038/nn.3466>

- Javadi, A. H., Emo, B., Howard, L. R., Zisch, F. E., Yu, Y., Knight, R., ... & Spiers, H. J. (2017). Hippocampal and prefrontal processing of network topology to simulate the future. *Nature communications*, 8(1), 14652. [https : //doi.org/10.1038/ncomms14652](https://doi.org/10.1038/ncomms14652)
- Jebara, N., Orriols, E., Zaoui, M., Berthoz, A., & Piolino, P. (2014). Effects of enactment in episodic memory: a pilot virtual reality study with young and elderly adults. *Frontiers in aging neuroscience*, 6, 338. [https : //doi.org/10.3389/fnagi.2014.00338](https://doi.org/10.3389/fnagi.2014.00338)
- Jerald, J., & Marks, R. (2016). Human-centered design for VR interactions. In ACM SIGGRAPH 2016 Courses (pp. 1-60).
- Kennedy, R. S., Lane, N. E., Berbaum, K. S., & Lilienthal, M. G. (1993). Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness. *The international journal of aviation psychology*, 3(3), 203-220.
- Konishi, K., & Bohbot, V. D. (2013). Spatial navigational strategies correlate with gray matter in the hippocampus of healthy older adults tested in a virtual maze. *Frontiers in aging neuroscience*, 1(5), 1-8. [https : //doi.org/10.3389/fnagi.2013.00001](https://doi.org/10.3389/fnagi.2013.00001)
- Lachman, M. E., & Agrigoroaei, S. (2012). Low perceived control as a risk factor for episodic memory: The mediational role of anxiety and task interference. *Memory & Cognition*, 40, 287-296. doi: 10.3758/s13421-011-0140-x
- Lewis, P. A., & Durrant, S. J. (2011). Overlapping memory replay during sleep builds cognitive schemata. *Trends in cognitive sciences*, 15(8), 343-351.
- Liang, Q., Liao, J., Li, J., Zheng, S., Jiang, X., & Huang, R. (2023). The role of the parahippocampal cortex in landmark-based distance estimation based on the contextual hypothesis. *Human Brain Mapping*, 44(1), 131-141.
- Liberti, L., Lavor, C., Maculan, N., & Mucherino, A. (2014). Euclidean distance geometry and applications. *SIAM review*, 56(1), 3-69. [https : //doi.org/10.1137/120875909](https://doi.org/10.1137/120875909)
- Lisman, J. E., & Grace, A. A. (2005). The hippocampal-VTA loop: controlling the entry of information into long-term memory. *Neuron*, 46(5), 703-713. [https : //doi.org/10.1016/j.neuron.2005.05.002](https://doi.org/10.1016/j.neuron.2005.05.002)
- Litman, J., Hutchins, T., and Russon, R. (2005). Epistemic curiosity, feeling-of-knowing, and exploratory behaviour. *Cogn. Emot.* 19, 559-582.

- Lockhart, S. N., Mayda, A. B., Roach, A. E., Fletcher, E., Carmichael, O., Maillard, P., ... & DeCarli, C. (2012). Episodic memory function is associated with multiple measures of white matter integrity in cognitive aging. *Frontiers in human neuroscience*, 6, 56. [https : //doi.org/10.3389/fnhum.2012.00056](https://doi.org/10.3389/fnhum.2012.00056)
- Loomis, J., & Knapp, J. (2003). Visual perception of egocentric distance in real and virtual environments. In L. J. Hettinger & M. W. Haas (Eds.), *Virtual and adaptive environments: Applications, implications, and human performance issues* (pp. 21–46). Lawrence Erlbaum Associates Publishers. <https://doi.org/10.1201/9781410608888.pt1>.
- O'Malley, M., Innes, A., & Wiener, J. M. (2018). How do we get there? Effects of cognitive aging on route memory. *Memory & Cognition*, 46, 274-284. [https : //doi.org/10.3758/s13421-017-0763-7](https://doi.org/10.3758/s13421-017-0763-7)
- Maguire, E. A., Gadian, D. G., Johnsrude, I. S., Good, C. D., Ashburner, J., Frackowiak, R. S., & Frith, C. D. (2000). Navigation-related structural change in the hippocampi of taxi drivers. *Proceedings of the National Academy of Sciences*, 97(8), 4398-4403. [https : //doi.org/10.1073/pnas.070039597](https://doi.org/10.1073/pnas.070039597)
- Makowski, D., Sperduti, M., Nicolas, S., & Piolino, P. (2017). “Being there” and remembering it: Presence improves memory encoding. *Consciousness and cognition*, 53, 194-202. doi: 10.1016/j.concog.2017.06.015
- Marchand, W. R., Lee, J. N., Suchy, Y., Garn, C., Johnson, S., Wood, N., & Chelune, G. (2011). Age-related changes of the functional architecture of the cortico-basal ganglia circuitry during motor task execution. *Neuroimage*, 55(1), 194-203. [https : //doi.org/10.1016/j.neuroimage.2010.12.030](https://doi.org/10.1016/j.neuroimage.2010.12.030)
- Moffat, S. D. (2009). Aging and spatial navigation: what do we know and where do we go?. *Neuropsychology review*, 19, 478-489. doi: 10.1007/s11065-009-9120-3
- Moser, E. I., Kropff, E., & Moser, M. B. (2008). Place cells, grid cells, and the brain's spatial representation system. *Annu. Rev. Neurosci.*, 31, 69-89.
- Münzer, S., Zimmer, H. D., Schwalm, M., Baus, J., & Aslan, I. (2006). Computer-assisted navigation and the acquisition of route and survey knowledge. *Journal of environmental psychology*, 26(4), 300-308. doi: <https://doi.org/10.1016/j.lindif.2009.05.001>
- Murcia-López, M., & Steed, A. (2016). The effect of environmental features, self-avatar, and immersion on object location memory in virtual environments. *Frontiers in ICT*, 3, 24. doi:10.3389/fict.2016.00024

- Nasreddine, Z. S., Phillips, N. A., Bédirian, V., Charbonneau, S., Whitehead, V., Collin, I., ... & Chertkow, H. (2005). The Montreal Cognitive Assessment, MoCA: a brief screening tool for mild cognitive impairment. *Journal of the American Geriatrics Society*, 53(4), 695-699. <https://doi.org/10.1111/j.1532-5415.2005.53221.x>
- Newcombe, N. S., Hegarty, M., & Uttal, D. (2023). Building a cognitive science of human variation: Individual differences in spatial navigation. *Topics in Cognitive Science*, 15(1), 6-14. <https://doi.org/10.1111/tops.12626>
- Novack, M., & Goldin-Meadow, S. (2015). Learning from gesture: How our hands change our minds. *Educational psychology review*, 27, 405-412. <https://doi.org/10.1007/s10648-015-9325-3>
- Park, D. C., & Reuter-Lorenz, P. (2009). The adaptive brain: aging and neurocognitive scaffolding. *Annual review of psychology*, 60(1), 173-196.
- Park, D. C., & Gutchess, A. H. (2004). Long-term memory and aging. *Cognitive neuroscience of aging: Linking cognitive and cerebral aging*, 218-245.
- Parush, A., Ahuvia-Pick, S., & Erev, I. (2007). Degradation in spatial knowledge acquisition when using automatic navigation systems. In S. Winter, M. Duckham, L. Kulik, & B. Kuipers (Eds.), *Spatial information theory* (pp. 238-254). Springer.
- Preston, A. R., & Eichenbaum, H. (2013). Interplay of hippocampus and prefrontal cortex in memory. *Current Biology*, 23(17), 764-773.
- Raz, N., Lindenberger, U., Rodrigue, K. M., Kennedy, K. M., Head, D., Williamson, A., ... & Acker, J. D. (2005). Regional brain changes in aging healthy adults: general trends, individual differences and modifiers. *Cerebral cortex*, 15(11), 1676-1689. <https://doi.org/10.1093/cercor/bhi044>
- Ruddle, R. A., Volkova, E., Mohler, B., & Bühlhoff, H. H. (2011). The effect of landmark and body-based sensory information on route knowledge. *Memory & cognition*, 39(4), 686-699. [doi: 10.3758/s13421-010-0054-z](https://doi.org/10.3758/s13421-010-0054-z)
- Ruggiero, G., Iachini, T., Ruotolo, F., & Senese, V. P. (2009). Spatial memory: The role of egocentric and allocentric frames of reference. In G. Allen (Ed.), *Spatial memory: Visuospatial processes, cognitive performance and developmental effects* (pp. 17-32). Nova Science Publishers.

- Rosenbaum, D. A., Chapman, K. M., Weigelt, M., Weiss, D. J., & van der Wel, R. (2012). Cognition, action, and object manipulation. *Psychological bulletin*, 138(5), 924. [https : //doi.org/10.1037/a0027839](https://doi.org/10.1037/a0027839)
- Richter, K. F., & Winter, S. (2014). Landmarks. Springer Cham Heidelberg New York Dordrecht London. doi, 10(978-3), 1.
- Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in cognitive sciences*, 20(9), 676-688. <https://doi.org/10.1016/j.tics.2016.07.002>
- Roettl, J., & Terlutter, R. (2018). The same video game in 2D, 3D or virtual reality—How does technology impact game evaluation and brand placements?. *PloS one*, 13(7), e0200724. doi: 10.1371/journal.pone.0200724
- Sakaki, M., Yagi, A., & Murayama, K. (2018). Curiosity in old age: A possible key to achieving adaptive aging. *Neuroscience & Biobehavioral Reviews*, 88, 106-116. [https : //doi.org/10.1016/j.neubiorev.2018.03.007](https://doi.org/10.1016/j.neubiorev.2018.03.007)
- Sauzéon, H., N’Kaoua, B., Arvind Pala, P., Taillade, M., & Guitton, P. (2016). Age and active navigation effects on episodic memory: A virtual reality study. *British Journal of Psychology*, 107(1), 72-94. [https : //doi.org/10.1111/bjop.12123](https://doi.org/10.1111/bjop.12123)
- Schubert, T., Friedmann, F., & Regenbrecht, H. (2001). The experience of presence: Factor analytic insights. *Presence: Teleoperators & Virtual Environments*, 10(3), 266-281.
- Sharp, P. E. (1999). Complimentary roles for hippocampal versus subicular/entorhinal place cells in coding place, context, and events. *Hippocampus*, 9(4), 432-443.
- Shin, J. D., Tang, W., & Jadhav, S. (2019). Dynamics of awake hippocampal-prefrontal replay for spatial learning and memory-guided decision making. *Neuron*, 104(6), 1110-1125. [https : //doi.org/10.1016/j.neuron.2019.09.012](https://doi.org/10.1016/j.neuron.2019.09.012)
- Shohamy, D., & Daw, N. D. (2015). Integrating memories to guide decisions. *Current Opinion in Behavioral Sciences*, 5, 85-90. [https : //doi.org/10.1016/j.cobeha.2015.08.010](https://doi.org/10.1016/j.cobeha.2015.08.010)
- Sivashankar, Y., Fernandes, M.A, Oudeyer, P. Y., & Sauzéon, H. (2024). The beneficial role of curiosity on route memory in children. *Frontiers in Cognition*, 3, 1-14.[https : //doi.org/10.3389/fcogn.2024.1346280](https://doi.org/10.3389/fcogn.2024.1346280)
- Sivashankar, Y., He, P., Sauzéon, H., & Fernandes, M. (2024). The benefit of motoric engagement at encoding on route memory. *Spatial Cognition and Computation*, 24(4), 271-296. doi: 10.1080/13875868.2024.2359929

- Sivashankar, Y., He, P., Tsapoytis, P., Skorski, E., & Fernandes, M. (2025; in press). The necessity of motoric engagement in enhancing route memory. *British Journal of Psychology*.
- Smith, P. F. (2017). The vestibular system and cognition. *Current opinion in neurology*, 30(1), 84-89. <https://doi.org/10.1097/WCO.0000000000000403>
- Smith, S. A., & Mulligan, N. W. (2021). Immersion, presence, and episodic memory in virtual reality environments. *Memory*, 29(8), 983-1005. doi: 10.1080/09658211.2021.1953535
- Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, 333(6043), 776-778. doi: 10.1126/science.1207745
- Sul, J. H., Kim, H., Huh, N., Lee, D., Jung, M. W. (2010). Distinct roles of rodent orbitofrontal and medial prefrontal cortex in decision making. *Neuron*, 66(3), 449-460. <https://doi.org/10.1016/j.neuron.2010.03.003>
- Sun, L., Frank, S. M., Epstein, R. A., Tse, P. U. (2021). The parahippocampal place area and hippocampus encode the spatial significance of landmark objects. *NeuroImage*, 236, 118081.
- Vinogradov, S., Luks, T. L., Simpson, G. V., Schulman, B. J., Glenn, S., & Wong, A. E. (2006). Brain activation patterns during memory of cognitive agency. *Neuroimage*, 31(2), 896-905. doi: 10.1016/j.neuroimage.2005.12.058
- Von Stülpnagel, R., & Steffens, M. C. (2012). Can active navigation be as good as driving? A comparison of spatial memory in drivers and backseat drivers. *Journal of experimental psychology: applied*, 18(2), 162. doi: 10.1037/a0027133
- Vorhees, C. V., & Williams, M. T. (2014). Assessing spatial learning and memory in rodents. *ILAR journal*, 55(2), 310-332. <https://doi.org/10.1093/ilar/ilu013>
- Waller, D., Loomis, J. M., & Haun, D. B. M. (2004). Body-based senses enhance knowledge of directions in large-scale environments. *Psychonomic Bulletin & Review*, 11, 157-163. doi: 10.3758/bf032064761
- Waller, D. E., & Nadel, L. E. (2013). Handbook of spatial cognition (pp. x-309). American Psychological Association. <https://doi.org/10.1037/13936-000>

- Ward, N. S., & Frackowiak, R. S. J. (2003). Age-related changes in the neural correlates of motor performance. *Brain*, *126*(4), 873-888. <https://doi.org/10.1093/brain/awg071>
- Weisberg, S. M., & Newcombe, N. S. (2016). How do (some) people make a cognitive map? Routes, places, and working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *42*(5), 768-778. <https://doi.org/10.1037/xlm0000200>
- Wiener, J. M., Kmecova, H., de Condappa, O. (2012). Route repetition and route re-tracing: effects of cognitive aging. *Frontiers in Aging Neuroscience*, *4*, 7. <https://doi.org/10.3389/fnagi.2012.00007>
- Wilson, P. (1999). Active exploration of a virtual environment does not promote orientation or memory for objects. *Environment and behavior*, *31*(6), 752-763.
- Wilson, P., Foreman, N., Gillett, R., & Stanton, D. (1997). Active versus passive processing of spatial information in a computer simulated environment. *Ecological psychology*, *9*(3), 207-222. <https://doi.org/10.1207/s15326969eco09033>
- Wilson, C. J., & Soranzo, A. (2015). The use of virtual reality in psychology: A case study in visual perception. *Computational and mathematical methods in medicine*, *2015*(1), 151702. <https://doi.org/10.1155/2015/151702>
- Zhu, S., Lakshminarasimhan, K. J., Arfaei, N., & Angelaki, D. E. (2022). Eye movements reveal spatiotemporal dynamics of visually-informed planning in navigation. *Elife*, *11*, e73097. <https://doi.org/10.7554/eLife.73097>

APPENDIX

Mathematical Description of Path Complexity Measure

Each trial has n timepoints. Participant location is recorded at each timepoint. Therefore, there are n position coordinates.

Let $p_i = (x_i, y_i)$ represent participant location at timepoint i , where $1 \leq i \leq n$.

With n position coordinates, there are $n - 1$ displacement vectors between consecutive position coordinates.

Let $d_j = (x_j - x_{j-1}, y_j - y_{j-1})$ be the displacement between timepoints $j - 1$ and j , where $2 \leq j \leq n$.

With $n - 1$ displacement vectors, there are $n - 2$ angles (turns) between consecutive displacement vectors.

Let $c_k = \text{complexity}(d_k, d_{k-1})$ be the complexity of the turn between non-zero displacement vectors d_k and d_{k-1} , where $3 \leq k \leq n$ and

$$\text{complexity}(a, b) = \min\left(\frac{2}{\pi} \cos^{-1}\left(\frac{a \cdot b}{\|a\| \|b\|}\right), 1\right) \quad (1)$$

If $a \cdot b = 0$, then $\text{complexity}(a, b) = 0$.

Therefore, total route complexity for a given trial is defined as

$$\frac{1}{n-2} \sum_{k=3}^n c_k \quad (2)$$